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An Explanatory analysis of first-term reenlistment modeling using the PerSMART data warehouse

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NAVAL POSTGRADUATE SCHOOL
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THESIS

AN EXPLANATORY ANALYSIS OF FIRST-TERM REENLISTMENT MODELING USING THE PERSMART DATA WAREHOUSE

by

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March 2002

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The Navy Bureau of Personnel has constructed a data warehouse (PerSMART) for use by Navy manpower planners. PerSMART is currently building a Retention Monitoring Module (RMM) intended to give Navy manpower planners a way of quickly assessing the impact of current and proposed policies on enlisted retention within the Navy. The purpose of this thesis is to examine the structure of PerSMART and identify possible data and models that could be useful in the construction of the Retention Modeling Module (RMM). The first part of this thesis conducts a literature review of studies looking at civilian and military retention and the effects of compensation, in particular Selective Reenlistment Bonuses (SRB), on retention. The second half of this thesis estimates and specifies a model examining the effects of SRBs on the retention behavior of Zone A sailors at the reenlistment decision point during fiscal years 1995-2001. The model shows a positive relationship exists between SRBs and retention. A one-unit increase in the SRB multiple was found to increase the probability of reenlistment by 3.6 percentage points on average. However, the marginal effect varied across rating groups from 0.8 to 10.4 percentage points. Finally, recommendations are given for future model specifications and sources of data.

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ABSTRACT

The Navy Bureau of Personnel has constructed a data warehouse (PerSMART) for use by Navy manpower planners. PerSMART is currently building a Retention Monitoring Module (RMM) intended to give Navy manpower planners a way of quickly assessing the impact of current and proposed policies on enlisted retention within the Navy. The purpose of this thesis is to examine the structure of PerSMART and identify possible data and models that could be useful in the construction of the Retention Modeling Module (RMM). The first part of this thesis conducts a literature review of studies looking at civilian and military retention and the effects of compensation, in particular Selective Reenlistment Bonuses (SRB), on retention. The second half of this thesis estimates and specifies a model examining the effects of SRBs on the retention behavior of Zone A sailors at the reenlistment decision point during fiscal years 1995-2001. The model shows a positive relationship exists between SRBs and retention. A one-unit increase in the SRB multiple was found to increase the probability of reenlistment by 3.6 percentage points on average. However, the marginal effect varied across rating groups from 0.8 to 10.4 percentage points. Finally, recommendations are given for future model specifications and sources of data.

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I. INTRODUCTION

A. BACKGROUND

In recent years manpower shortfalls within the Navy have highlighted a critical problem with the retention of sailors, especially first-term sailors. In 1999 Golding, Arkes, and Koopman, [Ref. 1] conducted research into the future manpower needs of the Navy. Using a 30-year forecast they predicted that technology would reduce the size of any required Naval fleet dramatically. This reduction would, in turn, necessitate the recruiting and retention of high quality sailors who would be capable of operating and maintaining complicated shipboard systems. So, while technology would reduce the number of personnel needed, the cost for those personnel would increase. The need for drastic change to the current pay system will be necessary in order to retain the sailor of the future. The enlisted force would shift from being predominately blue collar to being overwhelmingly white collar in make-up.

The widely publicized military/civilian pay gap has been identified as the main reason so many sailors choose to leave the Navy at the end of their first obligation rather than stay. [Ref 2] The retention problem has reached extreme proportions in many of the Navy's technology intensive ratings. [Ref. 2] With first-term attrition currently running at approximately 40 percent, solving the retention crisis has become a critical readiness issue.

Until recently the Navy did not have a single source, except the Enlisted Master File (EMF), from which essential personnel data, such as marital status, military pay, or sea time could be accumulated for use by Navy retention manpower planners. It is crucial that Navy leadership have current and accurate retention data in order to make informed decisions regarding personnel policies and initiate legislative action. To this end PerSMART, a personnel data warehouse, is currently under construction. PerSMART, which began in 1999, provides historical retention, reenlistment, and attrition statistics to manpower planners. [Ref. 3] Historical data can then be analyzed and used to predict likely future retention behavior. Historical data can also be used to predict future retention behavior by age cohorts, individual ratings, and groups of ratings.

The PerSMART data warehouse will also incorporate a Retention Monitoring System (RMS).

Classifying sailors by cohort and rating (or groups of ratings) could be especially useful when looking at the likely future intentions of sailors as they approach critical career milestones, such as their first End of Active Obligated Service (EAOS). The historical retention behavior of sailors in a particular Navy Enlisted Classification (NEC) code or rating maybe a good predictor of future behavior, holding constant external factors such as falling unemployment or a significant increase in the military/civilian pay gap.

As an enlisted data warehouse PerSMART collects both current and historical personnel data. This data warehouse maintains and facilitates access to personnel data by manpower planners. In the past this data was scattered across a wide spectrum of sources, some of which could not be accessed on a consistent or timely basis. To make matters worse, historical data was often not maintained, which further complicated the efforts of many would-be users. A key element of any successful data warehouse is the consistent and continual updating of information. This information needs to be placed in a standard format recognizable to most users. This allows manpower planners to make relatively timely predictions about future behavior. PerSMART is currently updated regularly from the EMF. Pre-selected data segments are then placed into fact tables representing various retention statistics. These fact tables are currently under construction. One problem has been the ability to locate information on military pay and allowances, as well as data on factors such as the amount of time a sailor has spent at sea. Much of the information must be pulled from multiple sources, which requires a significant investment of time and manpower.

One of the more important elements of retention has always been compensation. A wide variety of pay and allowances exist for sailors and are usually dependent upon the rating in which the sailor works. Changes in compensation can have far-reaching effects, which cannot be easily quantified in the absence of accurate historical data. Currently, the Selective Reenlistment Bonus (SRB) is one of the Navy's most cost effective retention tools. The SRB allows Navy manpower planners to target sailors with technical

skills who are likely to leave the service, and avoid over-compensating sailors who would likely stay even without an increase in pay. The SRB also improves the Navy's ability to respond quickly to an unforeseen retention crisis in a particular rating. [Ref 4] This is extremely important in an era of tight budgets and high operational demands. The SRB is reevaluated on an annual basis and changes within the fiscal year, based on current manning shortfalls.

In recent years, most notably FY 2000 and FY 2001, defense budgets have stressed the need for an increase in military compensation. Not only have monetary incentives such as base pay, SRB's, and sea pay been increased, but non-monetary compensation has been improved as well. Quality of life issues like better housing, more access to childcare, time off, reduced underway time, and increased health care services have been in the congressional spotlight. In order to better understand the effects of non-monetary compensation PerSMART will need to maintain information on personal demographics. The combination of these variables along with the monetary compensation variables will allow Navy manpower planners to formulate accurate behavioral models. These models will make up the core of a decision support system for use by both the military and civilian leadership of the Navy.

B. PURPOSE

As previously mentioned, when completed, the PerSMART data warehouse will consist of personnel data from a variety of sources. The main source is the EMF, but other sources should be examined as complements to the existing data. PerSMART contains a module known as the Retention Monitoring System (RMS). The purpose of RMS is to enable researchers to calculate retention rates for sailors according to their rating and personal demographic characteristics. In order to support the requirements of the RMS a Retention Modeling Module (RMM) is also currently under development. The RMM will contain various retention and reenlistment models utilizing different segments of the data sets contained in PerSMART. These retention models will use specific statistical analysis techniques and attempt to predict likely retention behavior given a specific set of individual, as well as aggregate, variables. The RMM will facilitate the analysis of specific proposed legislative changes as well as changes in the

external environment, such as the national unemployment rate. Using the RMM scenarios Navy manpower planners will be able to calculate the necessary SRB changes needed in order to offset factors that might cause drops in future retention. This would greatly improve the Navy's ability to meet current readiness requirements while retaining highly skilled sailors.

C. RESEARCH QUESTIONS

Currently PerSMART maintains data inputs from the EMF. The purpose of this study is to more fully explore those data inputs and to identify data sources other than the EMF that would be needed to augment the RMM. To this end this study seeks to answer the following questions:

- What data are needed to model retention behavior in a manner consistent with current literature on the topic?
- How well does the current structure of PerSMART support retention modeling?
- What data fields should be added to PerSMART to support retention modeling?
- What are the predicted effects of compensation on retention according to data elements that exist and/or may be incorporated into PerSMART?

D. SCOPE AND METHODOLOGY

This thesis conducts a thorough literature review of past and current retention studies focusing on relevant findings as well as on modeling approaches. The identification of various sources of data (such as civilian pay and unemployment rates) relevant to the proposed RMM is one of the main goals of this study. Finally, a retention model will be specified and estimated using data from PerSMART and standard modeling techniques. The model will reveal the strengths and weaknesses of the current data available in PerSMART (and in the EMF) to populate the RMM.

The methodology utilized in this thesis is as follows: (1) a thorough review all applicable books, articles, research studies, and other sources; (2) an audit of existing modeling techniques; and (3) the estimation of a multivariate retention model utilizing existing data from PerSMART.

E. ORGANIZATION OF STUDY

The remaining part of the thesis is organized into the following sections.

Chapter II. Theoretical Framework and Literature Review. This chapter provides an overview of the SRB program, describes the general structure of an Annualized Cost of Leaving (ACOL) model, and reviews past as well as current retention studies relevant to the estimation of a retention model.

Chapter III. Model Development. This chapter describes the analysis data set, the specification of a multivariate model for reenlistment, and the expected effects of explanatory variables on the probability of reenlisting.

Chapter IV. Data Analysis. This chapter discusses the analytical results of applying a multivariate retention model to the analysis data set.

Chapter V. Summary, Conclusions and Recommendations. This chapter summarizes the findings from the research and provides recommendations for future model specifications and sources of data.

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II. LITERATURE REVIEW

This chapter reviews various retention modeling approaches adopted by researchers of turnover of private sector workers. These approaches are compared to those adopted to model military turnover.

A. ANNUALIZED COST OF LEAVING (ACOL) MODEL OVERVIEW

The Annualized Cost of Leaving (ACOL) model was developed to allow researchers the ability to predict the future reenlistment behavior of service members at the End of Active Obligated Service (EAOS). The ACOL model is currently the primary model used by researchers to predict Navy retention behavior. Prior to the ACOL model, the Navy used historical continuation data to predict future retention. Historical data provided accurate predictions only when no important changes in economic factors were expected. The ACOL model explicitly hypothesizes that a service member's decision to reenlist is predicated on the perceived economic costs and benefits (or utility) of the alternatives realized from either reenlisting or leaving immediately.

The alternative occupational choices, military vs. civilian sectors, differ in terms of monetary factors such as salary, fringe benefits, and non-monetary factors such as job satisfaction, time off, job related stress, and the work environment. The decision to reenlist or leave is based upon which combination yields the most utility (or net economic benefits) to the service member.

The ACOL model relies on the assumption that individuals behave rationally, and that people will attempt to maximize benefits when making their decision to stay or leave. [Ref. 5] ACOL takes into account expected future earnings and assigns monetary values to the non-monetary compensation items. These expected future earnings are then discounted into present values. The annualized cost of leaving is the difference between the present value of both the military and civilian options, expressed on an annual basis over the future time horizon. When ACOL is positive then the model assumes that the service member will reenlist; when it is negative the service member will leave active duty.

> One searches over all possible lengths of stay to determine the optimal length of stay at a given decision point. The financial returns

associated with the optimal length of stay are then compared with the financial incentive of leaving immediately. The ACOL value is the net financial incentive to stay if positive or leave if negative. It is calculated as the annualized difference in the financial rewards from staying to the optimal leaving point relative to leaving immediately. [Ref. 6]

Warner and Asch provided a mathematical statement of the ACOL model. [Ref. 7] The ACOL model incorporates the following variables when explaining an individual's decision to stay or leave:

W^M_j = expected military pay in each future year *j*

$W^C_{j,t}$ = expected civilian earnings in future year j if the individual retires at time t

$W^C_{j,n}$ = expected civilian earnings in future year j if the individual separates after future year n

R_n = expected present value at future year n of retired pay and other separation benefits if the individual separates after future year n

R_t = expected present value at year t of retired pay and other separation benefits if the individual leaves now

τ^m = preference for the military lifestyle

τ^c = preference for the civilian lifestyle

ρ = the individual's subjective discount rate on future income

$S_{t,n}$ = the present value of the future benefit from staying from period t to period n

L_t = the value of leaving immediately

$C_{t,n}$ = the cost of leaving

The present value of the future benefit of staying from period t through period n ($S_{t,n}$) is calculated in the model as follows:

$$S_{t,n} = \sum \frac{W_j^M}{(1+\rho)^{j-t}} + \frac{R_n}{(1+\rho)^{n-t}} + \sum_{j=t+1}^{n} \frac{\tau^m}{(1+\rho)^{j-t}} + \sum_{j=n+1}^{\infty} \frac{W_{j,n}^C + \tau^c}{(1+\rho)^{j-t}}$$

Thus, if the individual stays to some future point, n, he accrues military pay (W^M_j), the monetary equivalent of non-pecuniary benefits, and retirement pay (R_n).

Since, ACOL is a utility maximization model, the individuals "taste" for the military lifestyle, τ^m, must also be counted.

The value of leaving immediately is given by:

$$L_t = \sum_{j=n+1}^{\infty} \frac{W_{j,t}^C + \tau^c}{(1+\rho)^{j-t}} + R_t$$

The Annualized Cost of Leaving (ACOL) is ($S_{t,n} - L_t$). A positive value of ACOL over any time horizon predicts that the service member reenlists. A negative value of ACOL predicts that the service member leaves. The ACOL model is the most widely used model when trying to predict future retention for the Navy today.

B. SRB PROGRAM OVERVIEW AND ZONES

The ACOL model incorporates mostly economic factors in the formulation. One of the monetary factors that varies across ratings is the Selective Reenlistment Bonus (SRB). Variations in SRB are a key source of variation in military pay in the ACOL model.

The SRB is offered to enlisted members in critical skills, those facing manning shortages, as needed in order to achieve retention goals. Enlisted members who elect to receive the SRB are obligated for a specific length of service in the rating for which the SRB is paid. The SRB program not only allows the Navy to address manning shortfalls in critical ratings but also reduces total cost of personnel to the Navy. Personnel cost savings come in the form of saved replacement costs and by allowing the Navy to pay only those members in ratings where retention is below acceptable minimums.

SRB levels are reviewed periodically to determine the amount of SRB to be authorized for each skill/rating group. This allows the Navy to adjust SRB levels as retention levels and readiness conditions dictate.

Skill groups are assigned criticality factors ranging from 0 to 15. These factors are then multiplied by the service member's monthly base pay and years of obligated service to be incurred. The resulting product is the dollar amount of SRB that the service member can receive. The payment, however, cannot exceed predetermined levels authorized by Congress. The current SRB maximum mandated by Congress is 60,000

dollars. The electing service member receives 50 percent of the SRB at the initial service obligation and the rest is paid out in equal annual installments for the duration of obligated service.

Three zones of eligibility exist for the SRB. Zone A consists of those service members currently having between 21 months and six years of active duty. Zone A covers those sailors at the end of their first obligation. Zone B consists of service members currently having between six years and ten years of active duty (the second term reenlistment point), and Zone C consists of those members currently having between ten years and 14 years of active duty (the third term reenlistment point). Each zone has different SRB factors used to determine SRB levels. Only one SRB may be awarded per enlistment and each SRB service obligation must take the service member into the next SRB zone.

Minimum eligibility requirements must be met in order to receive the SRB. The service member must have attained the rank of E-3 at the time of obligation of service and must be within three months of discharge from active duty when reenlisting or extending.

C. LITERATURE REVIEW

Among the major challenges facing today's Navy is the fight to attract and retain high quality personnel. High turnover rates have forced the Navy to increase funding for both retention and recruiting while pulling funds away from acquisition and readiness programs needed to prepare the force for a new era of warfare and the "war on terrorism." The effect has been to produce a shortage of funds across the board in most major programs. Recent defense budgets have acknowledged the shortfalls and funding levels have risen. Despite this, it is imperative that the Navy continue research on critical topics such as turnover and compensation.

While this thesis deals with military retention, it also may be useful to look at turnover and compensation factors as they pertain to retention behavior associated with civilian organizations. Some factors may elicit the same retention response across all spectrums of workers. The first two sections of this literature review examine studies aimed at the civilian sector provide an overview of key factors that have been shown to

affect retention behavior. The final section looks specifically at studies of the military with specific emphasis on the effects of compensation on retention behavior.

1. Non-Economic Studies of Retention in Non-Military Organizations

In 1977 Mobley [Ref. 8], expanding on past research into the resignation process, suggested that far more was involved in the decision to quit than simple job dissatisfaction. Mobley believed that negative attitudes toward one's job led to thoughts of quitting. At this point the individual would begin to investigate the consequences of actually quitting. Some factors likely to be examined would be the likelihood of finding another job of equal or greater perceived value, the cost of quitting to the individual and how extensive the job search would likely be. If the individual believed that the chances of finding a favorable job were high then the actual search for new employment opportunities would begin in earnest. The end result would be the individual actually finding alternative employment and quitting the current job. Mobley, Homer, and Hollingsworth [Ref. 9] looked at Mobley's previous research and concluded that job dissatisfaction has an effect on thoughts of quitting but very little influence on the actual act of quitting.

The role individual expectations play in the turnover process was investigated by Porter and Steers [Ref. 10] in 1973. When an individual takes a position within an organization there likely exists expectations the individual brings along. Porter and Steers found a positive correlation between job satisfaction and met expectations. The number of employees who stay with an organization increases as the perception of met expectations increases. The conclusion was that expectations greatly influence the turnover process.

In 1994 Lee and Mitchell [Ref. 11] expanded the area of turnover research by proposing the idea of a shock to the system influencing the turnover process. Previous research had focused on job satisfaction variables as the main factors in employee turnover. The model suggested that the employee first experiences a shock to the system in the form of a traumatic event. This event causes the employee to begin participation in the turnover process, which leads to actual turnover. The model suggested four possible paths affecting the turnover event.

In the first scenario the shock simply pushes the employee to rethink past experiences with the turnover process and this in turn starts the employee thinking about applying the past experience to the current situation. In the second scenario the employee is so traumatized by the shock that he questions his fit within the organization as well as his commitment to it. If the employee decides that a negative situation exists he quits without participating in the lengthy turnover process. The third scenario starts the employee on the traditional path of the turnover process. In the fourth scenario the employee experiences no shocks to the system. The employee simply becomes dissatisfied and begins the turnover process. One difference here is that the employee is as likely to quit abruptly as he is to follow the traditional turnover process.

In 1996 Lee, Mitchell, Wise, and Fireman followed up on Lee and Mitchell's previous work. [Ref.12] Researchers conducted a series of interviews with 44 nurses who had voluntarily left their jobs. This research, while failing to validate all of Lee and Mitchell's previous findings, did support their model. Some 45 percent of the interviewees indicated that they had left jobs without waiting for follow on employment opportunities. Fifty-five percent of the interviewees followed the traditional course of the turnover process and 58 percent stated that some kind of trauma inducing event had precipitated the decision to leave.

2. Other Non-Economic Studies of Turnover

Turnover is the process by which employees end their relationship with the organization. Turnover is not simply the act of quitting one's job. Pearson [Ref. 13] explains turnover as the combination of variables leading to the decision to terminate employment and the behavior displayed while coming to the actual decision.

Arnold and Feldman [Ref. 14] noted that most studies directed at explaining the turnover phenomenon rely on similar sets of variables, including job attitudes (e.g., satisfaction, commitment) and demographic variables (e.g., marital status, age). They found that the model with the greatest explanatory value (R = .44) contained the following significant individual predictor variables: tenure, job satisfaction, perceived job security, and intention to search for an alternate position. These variables are easily obtained and could provide great value in predicting future turnover rates.

Aggregate turnover, as defined as the turnover rate of an organization, appears to be strongly correlated with aggregate economic data such as the unemployment rate. However, Cotton and Tuttle [Ref. 15] found that aggregate national economic data did not correlate well with individual turnover behavior. They concluded that while the unemployment rate might be useful in understanding organizational turnover it is not reliable in helping to predict an individual's probability of staying with the organization in question. However many other economic studies have found just the opposite to be true.

Employee turnover within an organization falls into two separate categories: voluntary and involuntary. McEvoy and Cascio [Ref. 16] described the voluntary turnover process resulting in resignation, and the involuntary turnover process resulting from a disability, layoff or mandatory retirement. What is not clear is the role organizational culture and direction setting played in the turnover process. Much of the current turnover research suggests that organizational human resource policies, such as retirement programs, health benefits, and incentive pay programs, have a significant impact on the voluntary turnover process as well. [Ref. 6]

One major problem faced when researching the turnover process is in understanding the motivation behind it. Voluntary turnover has both positive and negative effects on the participants. [Ref. 17] For the organization it can increase inefficiency, costs, training requirements, and recruiting efforts. Turnover also interrupts the natural rhythm associated with groups of employees who are used to working together for long periods of time. Involuntary turnover can cut costs and improve morale by increasing promotion opportunities. However, voluntary turnover can have positive effects on the organization as well. If turnover increases promotion opportunities for those who stay, organizational morale will improve as well.

The individual participant in the turnover process, both voluntary as well as involuntary, can experience negative side effects such as a loss of seniority, benefits, prestige, self-esteem, and monetary compensation. At the other end of the spectrum are positive effects such as finding a better job, more money, increased self-esteem, improved family relationships, and less stress.

Turnover within an organization is unavoidable and at times necessary. The goal of understanding the turnover process is to provide organizations with the ability to better control voluntary turnover in order to maintain positive control over the turnover process. However, the turnover process differs greatly when comparing the military or military-like organizations with non-military organizations. Since culture and human resource policies differ greatly between civilian and military organizations it seems likely that the turnover process would differ greatly as well. Because of this difference it is necessary to clearly define the differences between the two styles.

3. Turnover in Military Organizations

Military organizations operate under somewhat different circumstances than non-military organizations. When an individual decides to accept employment with the military he volunteers for duty for a contractual period of time. While the length of time may vary from person to person the requirements for termination of employment do not. Other than being administratively separated for poor performance or violations of the Uniform Code of Military Justice (UCMJ), the individual service member has very few avenues by which to legally turnover prior to their EAOS. This does not preclude the member from participating in the traditional turnover process; however, it simply implies a longer time frame over which the process unfolds. While this seems to suggest that an individual joining the military commits more than does his civilian counterpart, very little research has been done to support this assumption. Most research pertaining to military turnover focuses on compensation and quality of life issues when trying to explain military turnover. The ACOL model has been the most widely used tool when trying to explain retention behavior in the military.

Cymrot [Ref.18] looked at the effects of selected reenlistment bonuses (SRB's) on reenlistment in the Marine Corps. Using the Annualized Cost of Living (ACOL), model Cymrot aggregated marine occupational specialties into 22 groups and assumed that individuals in comparable skill groups would have similar responses to the SRB. Cymrot divided each group into the same zones the military uses to differentiate between skill levels when determining who is eligible for bonuses. Sailors between 21 months and six years are in Zone A; sailors with between six and ten years of service are in Zone B; and

Zone C consists of sailors with between ten and 14 years of service. Cymrot found that the SRB multiple was positively correlated with reenlistment in each group and zone. For example, if the SRB multiple for Zone A was increased from zero to one for any skill set, Cymrot found that reenlistment rates increased by more than 13 percent. Cymrot also found that the national unemployment rate had an effect on reenlistment in Zone A but not in Zones B and C. A one percent increase in the unemployment rate resulted in a 4.3 percent increase in retention of members in Zone A.

Mehay's 2001 survey of existing retention studies on retention [Ref. 19] describes one of the earliest efforts at using ACOL by Warner and Goldberg. [Ref. 20] Using five years of data (1974-78), the authors looked at reenlistment decisions of first term Navy personnel. Navy ratings were divided into 16 separate groups based on similarities of training, job requirements, and working conditions, and retention models were estimated for each group. Some of the variables used were the ACOL variable, SRB multiple, marital status, and the national unemployment rate in the month of each member's decision.

Warner and Goldberg concluded that the value of ACOL was a maximum at the four-year reenlistment point. This implied that retirement pay was not a significant factor in the decision to reenlist by sailors in the first term. Their pay elasticities averaged 2.35 across all 16 groups. The average effect of a one-level increase in SRB on the predicted reenlistment rate was a 3.2 percentage point increase across all groups.

Warner and Goldberg also found that the pay elasticity was significantly influenced by expected sea duty. Expected sea duty was defined as the proportion of personnel in an individual's rating who were assigned to sea duty in the next four length of service (LOS) cells immediately following the LOS cell of the sailor at the decision point. For groups whose members expected greater amounts of sea duty during their next tour the pay effects were less elastic. That is, the effect of a given change in military pay was smaller in ratings with higher expected sea duty. Further, the fraction of time spent on sea duty had a significantly negative effect on first-term reenlistment rates. They also found that marital status was a significant predictor; their model predicted a higher reenlistment rate for married service members compared to single service members.

In 2001 Goldberg conducted a survey of military reenlistment research titled "A Survey of Enlisted Retention: Models and Findings". [Ref. 21] Goldberg focused on estimated first-term pay elasticities as well as the effects of one-level SRB increases on enlisted retention in the literature. His survey of pay elasticities and SRB effects are reproduced in Table 2.1. Goldberg found that the majority of first-term pay elasticity estimates in the literature are between 1.2 and 2.2. The estimated effects of a one-level increase in the SRB on reenlistment rates across the military in the literature range between 1.5 and 3.0. Estimates vary greatly depending on whether or not the study used grouped or individual data and the exact specification of the estimating model.

Goldberg noted that some retention models contain variables other than pay, such as the civilian unemployment rate, and various demographic variables including marital status, race, education, and aptitude. One concern when these variables are included in the model is that they are often used to predict civilian pay, which is then used to compute the military-civilian pay ratio or the ACOL variable. This can cause multicollinearity, increasing the variance of the estimated coefficient of relative pay. If the purpose of the model is to explain the effect of pay on retention one might want to exclude personal demographic variables from the model. However, it should be noted that the estimated parameter on pay will still be unbiased in the presence of multicollinearity.

In 1992 Cooke and Quester [Ref. 22] used logit models to find a relationship between a recruit's background traits and the completion of obligated service. Using only Navy first-term male recruits who enlisted for four years between 1978 and 1982, Cooke and Quester looked at the predictive value of background characteristics on success in the Navy. Success was defined as completing the initial enlistment, being eligible to reenlist, and either reenlisting or extending the service contract. What they found was that AFQT category and High School Diploma Status (HSDG) were highly significant when predicting retention with this particular set of recruits. This study showed that high school graduation, above average Armed Forces Qualification Test Battery (AFQT) scores, and participation in the Delayed Entry Program (DEP) were all associated with a higher propensity for success in the Navy.

Table 2.1. First-Term Pay Elasticities from Various Studies.

Study	Pay Variable	Sample Restrictions	Pay Elasticity	SRB Effect*
Black, Hogan, and Sylwester (1987)	ACOL-2; but elasticity of reenlistment with respect to military pay	Navy enlisted	0.8-0.9	
Cooke, Marcus, and Quester (1992)	Military/civilian pay index; SRB	Navy enlisted	1.6	2.5 (I)
Daula and Moffitt (1991)	Military/civilian pay difference	Army infantry	1.2	
Daula and Moffitt (1995)	Military/civilian pay difference	Army infantry	0.5	
	Military pay alone	Army infantry	2.2	
	ACOL-2	Army infantry	0.8	
Goldberg and Warner (1982)	Total retention; military pay alone (RMC)	Navy enlisted, by occupational group	1.1-2.7	1.5-3.0 (I) 2.0-3.9 (L)
Hosek and Peterson (1985)	Military/civilian pay index; SRB	Enlisted males; four services	3.6	1.8 (I) 2.5 (L)
Mackin (1996)	ACOL-2; but elasticity of reenlistment with respect to military pay	Army enlisted Navy enlisted USAF enlisted USMC enlisted	1.2 1.0 0.5 1.4	
Mackin et al. (1996), conditional logit model	Reenlistment; Military pay alone	Navy enlisted; by occupational group	0.2-1.5	0.4-2.8 (I)
	Total retention; Military pay alone		0.2-0.9	
Shiells and McMahon (1993)	Military/civilian pay index;SRB	Navy enlisted	1.9	
Smith et al. (1991)	Military pay alone	Army infantry	1.3	2.2 (I)
		Army maintenance	1.8	
		Army administration	1.9	
Warner and Goldberg (1984)	Military pay alone (SRB)	Navy enlisted, by occupational group	1.1-3.4	1.8-5.5 (I)
Warner and Solon (1991)	ACOL; but elasticity of reenlistment with respect to military pay	Army infantry	1.2	

*SRB effect on reenlistment (*not* total retention) rate is measured in percentage points, payment type = installment (I) or lump-sum (L).
Source: [Ref. 21]

Doering and Grissmer [Ref. 23] conducted a study in 1985 and concluded that pay grade was the single most important factor when trying to explain military retention. That same year Goldberg [Ref. 24] conducted a study looking at the effect military compensation and employment opportunities in the civilian market had on military retention for enlisted service members. Military compensation had a significant effect on retention while civilian employment opportunities were not statistically significant.

Boesel and Johnson analyzed the effects of family size and marital status on retention. [Ref. 25] Their literature review of existing studies concluded that married members and married members with children were more likely to separate. However, numerous other researchers have contradicted these conclusions. In particular, Buddin (1981) and Greenberg (1977) found just the opposite to be true, as did Warner and Goldberg (1984). [Ref. 20] The model estimated in this thesis concurs with the hypothesis that married members are more likely to stay then their single counterparts.

Quality of life issues took on new importance during the 1990's. In 1998 the General Accounting Office (GAO) looked at this issue at the behest of Congress. As the size of the Navy's deployable force structure shrank and commitments remained the same a new trend began to emerge. Forced to accomplish the same commitments with less, Navy force structure had begun to increase the operations tempo of its ships. Initially the impact on retention was hardly noticeable. Late in the 1990s, when the drawdown was beginning to come to an end, people were still being pushed out. However, as soon as the drawdown was complete and the force size stabilized, retention dropped to an all time low. The GAO's survey found that base pay was only one of many factors cited by personnel who stated they intended to leave the Navy. Other factors included, access to childcare, deployment schedules, the amount of liberty, and increasing numbers of gapped billets (which created more work for everyone else).

In 1999 two RAND Corporation researchers, Asch and Hosek [Ref. 26], examined the effects of long duty on retention. Long duty was defined as 30 or more consecutive days of separation. They found that long duty resulted in decreased retention among first-term sailors. Implications of their findings are that sea duty could be a cause

of lowered retention rates for first-term sailors, since sailors on sea duty often experience long periods of separation.

Comparing military to civilian pay takes into account education levels and occupational fields. It does not factor in the risks associated with military service. Risk, while not accounted for, nonetheless raises the reservation wage for individuals considering military service. Asch and Hosek advised that enlisted pay should be above that of the civilian counterpart in order to retain motivated personnel and maintain readiness.

In 2000 Hansen [Ref. 27] examined the manning levels among enlisted ratings to see if manning shortfalls in enlisted ratings were linked to the civilian earnings potential of workers in each occupation. Civilian opportunities vary greatly between ratings and, as expected, technical ratings had the best civilian opportunities and the biggest manning shortfalls in the Navy.

Hansen compared the enlisted pay actually received by an individual in a specific rating to the compensation received by civilians in comparable occupations. He noted that it can be difficult to accurately match Navy enlisted ratings to a civilian counterpart. For example, a Navy Mess Management Specialist has a direct counterpart in many civilian food service specialties, where as a Gunners Mate does not. Hansen used the Defense Manpower Data Center's (DMDC) conversion manual to link Navy ratings to an Occupational Employment Statistics (OES) code used to identify civilian occupations. This is one of the very few sources of information on rating-specific civilian earnings data.

Hansen found a positive correlation between military compensation and actual reenlistment. Hansen believed that SRBs would be the most sensible way to induce higher reenlistment, especially among the high-demand technical ratings or those that are critically undermanned.

As previously discussed, military turnover and retention behavior differs from that of workers in comparable civilian organizations. Legal service obligations, the risks associated with military service, and the individual's sense of duty, are all unique aspects

of military organizations that affect retention. However, individual responses to factors like compensation, unemployment rates and quality of life may be similar.

The studies reviewed here represent a cross-section of the type and scope of research that has been conducted for the purpose of understanding turnover and retention behavior of military service members. The current research suggests that data such as military pay (including SRBs), personal demographic variables (marital status, number of dependents, race, and aptitude), and external economic factors such the unemployment rate are essential to any model examining military retention behavior. Further, the review shows that the ACOL approach is an essential modeling technique when looking at military retention and turnover. Finally, the review shows that the SRB is a highly significant variable in models predicting retention.

III. MODEL DEVELOPMENT

A. INTRODUCTION

In this chapter we describe the process of specifying a multivariate model of reenlistment behavior. The model is designed to utilize data available from the Retention Monitoring System (RMS) contained in PerSMART, and emphasis is made on the examination of the specific effects that Selective Reenlistment Bonuses (SRBs) have on first term reenlistment decisions. Analysis of the multivariate model will determine the predicted probability that an enlisted person in SRB Zone A will reenlist based on selected independent variables.

SAG Corporation, who helped develop the PerSMART data warehouse, provided the data set analyzed. The data were extracted from a number of separate tables in the RMS. The data set contained selected Enlisted Master File (EMF) information on the 389,921 enlisted members who extended, reenlisted, or left the Navy during fiscal years 1995 through 2001. The Appendix provides definitions of the data fields contained in the RMS extract. Since the RMS was not designed to be a research database, the model and data used in this analysis will examine the strengths and weaknesses of the current PerSMART structure in supporting retention modeling. [Ref. 28]

B. DATA RESTRICTIONS

This analysis is concerned specifically with those individuals who are considered to be in SRB Zone A when they are making their reenlistment decisions. Zone A is defined to include sailors who have at least 21 months and no more than six years of active duty service. Some enlisted members may still be in service schools or other training courses at the 21-month point and would not share the same military experiences as the majority of sailors who have served in the fleet prior to their decision points. Thus, the final data set included only those with at least two and no more than six years of service.

Some sailors may not be eligible for reenlistment at their decision point for a number of administrative reasons. Weight control problems, misconduct, and drug use are just a few of the conditions that make a sailor ineligible for reenlistment

consideration. If a sailor is not eligible to reenlist, then he or she is not eligible for an SRB. Loss and reenlistment codes from the RMS extract data set (Dod_Loss_Code, Navy_Loss_Rqc) allow the researcher to identify those who are not eligible to reenlist. To better analyze the effects of SRBs on reenlistment, only those individuals who were voluntarily released or discharged at the completion of their required active duty service and were eligible for reenlistment or preferred reenlistment were included in the data set as leavers. Taking into account all constraints that were made to this point, the data set included 179,316 Zone A sailors who reenlisted, extended, or separated from fiscal years 1995-2001.

At the reenlistment decision point, some sailors may choose to extend their enlistment contracts rather than reenlist for another full term. These extensions may be short or long term. Short-term extensions may be from one to 23 months long and are generally executed for administrative reasons, such as for continued maternity benefits, or to match the end of service obligation to the projected rotation date from the current duty assignment. Long-term extensions are from 24 to 48 months and are often taken for a variety of reasons, including shorter commitments or delays of reenlistment to receive bonuses in tax-exempt combat zones. Sailors who are not eligible to reenlist cannot extend, and extenders are not eligible to receive an SRB. Since the decision to extend is not the same as the decision to reenlist, and since the focus of this analysis is on the effects of SRBs, people who extended were deleted from the analysis data set using the data field "code." This field describes the reenlistment decision and was assigned to each observation when the data set was extracted from the RMS. It identifies whether a sailor extended ("code" = 3), reenlisted ("code" = 4) or separated ("code" = 7). The final analysis data set that included only Zone A sailors who reenlisted or separated in fiscal years 1995-2001 contained 173,735 observations. In other words, 5,581 Zone A sailors extended their enlistment contracts during this period.

C. MODEL SPECIFICATION

1. Dependent Variable

The purpose of the multivariate model is to analyze the independent effects of selected explanatory variables on the decision to reenlist. Consequently, the dependent

variable for the model is constructed as a dichotomous variable representing an individual's decision to either reenlist or leave the Navy. The variable REENL is coded as a '1' if the sailor reenlists and as a '0' if the sailor chooses to separate.

2. Explanatory Variables

Specification of the retention model is based primarily on the literature reviewed in Chapter II and on the availability of data for the variables from both the original data set and other sources. Based on prior studies of military retention, a preliminary model of reenlistment for Zone A Navy enlisted members can be specified as follows:

$$\textbf{Reenlistment} = \mathbf{f}\ (\mathbf{ACOL}, \mathbf{X_1}, \ldots, \mathbf{X_k}).$$

ACOL is the Annualized Cost of Leaving variable that estimates the present value of the individual's net economic benefits associated with leaving the service at a decision point, and the Xs represent the other *k* independent variables that are expected to have an effect on reenlistment. Such variables may include expected sea duty, gender, family status, race, Selective Reenlistment Bonuses, civilian unemployment rates, education, and aptitude test scores (AFQT). The individual variables actually used to specify the model in this thesis are described in the following sections.

a. Paygrade

When specifying a variable to be used to analyze the effects of pay on reenlistment, the literature supports either an ACOL variable or a military-civilian pay ratio. The ACOL approach is complex, requiring multiple sources of data to accurately calculate a value that estimates the net economic benefits of either staying over a future period or leaving immediately. To perform these calculations, ACOL programming must be able to project civilian earnings over the selected future horizon. It must also project future military earnings, using historical promotion rates, over the same horizon. These future earnings streams must be discounted to present values and require personal discount factors, Consumer Price Index (CPI) deflators, and estimates of the relevant time horizon, none of which are included in the data contained in the RMS. A common problem associated with using an ACOL model is the difficulty in estimating and updating the expected civilian earnings streams. [Ref. 29, Ref. 30] There are usually variations in how civilian earnings and military pay are estimated and incorporated in an

ACOL variable, and it is not clear that the procedure for estimating and updating the ACOL variable can be easily automated for use in the RMS. [Ref. 28]

In his 2001 survey of retention models, Mehay [Ref. 19] mentions two methods for calculating military-civilian pay ratios or indices. The first and most widely used method calculates the current civilian earnings of veterans averaged across all of their respective civilian occupations. This method provides a current measure of civilian pay that is more easily calculated than ACOL. Also, averaging civilian pay over occupations may reduce selection bias because the civilian occupation that military leavers enter may be an outcome of this selection process. [Ref. 19] An alternative method is to calculate the pay ratio on an occupation-specific basis. This method uses a conversion index to match military occupations to civilian occupations as classified in the monthly Current Population Surveys (CPS). The CPS can then provide the average earnings for the civilian occupation(s) that is (are) comparable to each Navy rating. Hansen [Ref. 27] used this method in 2000 and found that some ratings do not have clear civilian counterparts, and some civilian occupations have too few observations to provide useful earnings data.

A potential problem with using civilian pay comparisons in a retention model is the inclusion of variables for personal characteristics, including race, education, aptitude, or marital status, in the same model. These characteristics are typically used to predict the civilian earnings component of the ACOL variable and thus may cause multicollinearity problems in a retention model. [Ref. 21, Ref. 27] Mehay's survey [Ref. 19] provides further discussion of this issue.

Calculating a military-civilian pay ratio for each rating for every decision period contained in the analysis data set was a problem for this thesis. The procedures required to calculate this ratio, or an ACOL variable, are beyond the scope of this thesis. However, data contained in the RMS do allow for a convenient merging of historical military pay information into the data set. The time period of a sailor's decision point can be matched to a calendar year, and this can be used with paygrade and years of service to determine the base pay for a sailor when he or she made a reenlistment decision. However, a potential problem with using a simple military pay variable was discovered

during an initial analysis of the monthly base pay variable created for this data set. The problem was there was little variation in the pay variable across the observations, since the vast majority (74.4 percent) of sailors in Zone A were in only two paygrades--E-4 and E-5. Thus, to best capture the effects of military pay in this model, paygrade variables were used as proxies for military pay. The variable E3B is coded as '1' if the sailor is in paygrades E-1 through E-3 and '0' otherwise. The variables "E4," "E5," and "E6" are coded as '1' if the sailor is in either one of the respective paygrades and '0' otherwise. The paygrade variables are expected to have a positive effect on reenlistment when compared to lower paygrades and a negative effect when compared to a higher paygrade. For example, an E-4 is expected to be more likely to reenlist than an E-3 or below but less likely to reenlist than an E-5.

b. Sea/Shore Duty

In 1984, Warner and Goldberg [Ref. 20] used a variable to examine the effect of expected sea duty on a sailor's decision to reenlist. Their sea duty variable was defined as the proportion of personnel in a sailor's rating who were on sea duty in the next four Length Of Service (LOS) groups (years) following the sailor's LOS group (year of service) at the decision point. They found that higher expected sea duty proportions in a given rating have a significant negative effect on first-term reenlistment rates. That is, those sailors who faced the prospect of greater time at sea if they reenlisted were less likely to reenlist. They interpreted this result to reflect the net distaste for sea duty and the accompanying family separation.

Unlike the sea duty variable used by Warner and Goldberg, the sea/shore duty variables used in this model are not related to prospective sea duty. While we agree that the rigors of sea duty tend to reduce a sailor's propensity to reenlist, it is also possible that currently serving on shore duty (at the EAOS point) will tend to increase the reenlistment propensity, even if one faces the prospect of returning to sea. Using an expected sea duty variable, as in Warner and Goldberg, assumes that a sailor at EAOS who is nearing the end of a shore duty assignment would be less likely to reenlist than a sailor at EAOS who is approaching the end of a sea duty assignment. However, an opposite outcome is plausible: current shore duty may make service members "forget"

the negative aspects of sea duty, which occurred some time in the past, and thus make them more willing to reenlist than those currently on sea duty. Generally, we expect sailors currently serving on shore to be more willing to reenlist, even if they do face extensive sea duty during the reenlistment term.

The field "Onboard_Ss" from the RMS data set describes whether an individual was on sea, shore, or neutral duty at the time of his or her reenlistment decision. Neutral duty is a type of shore duty that does not count against the shore portion of a required sea-shore rotation. As such, neutral duty is considered shore duty for this analysis. The variable we created, SEA, is coded as '1' if the sailor was in a sea duty billet at the decision point and '0' if the billet was shore duty. The variable SHORE is coded just the opposite of SEA. These variables were created for use in different models where the comparison group is the majority of the sample. For example, if the majority of sailors in the analysis sample currently were assigned to shore duty billets, the variable SEA would be used in the model to examine the effects of being in the minority group. Conversely, the variable SHORE would be used if the majority currently were assigned to sea duty billets. Based on previous findings of sea duty effects and on anecdotal evidence, the hypotheses for these variables are that SEA will be negatively related to reenlistment compared to SHORE, or that SHORE will be positively related to reenlistment compared to SEA.

c. Gender

The variable FEMALE is used to examine the effects of gender on reenlistment. FEMALE is coded as '1' if the individual is a woman and '0' if he is a man. Prior studies have shown that women have a higher propensity to reenlist than men. [Ref. 7, Ref. 29] This may possibly be attributed to increased opportunities for women in the military as compared to the civilian sector. Consequently, the hypothesis for this variable is that a woman will be more likely to reenlist than a man.

d. Family Status

The family status variables used in this model were created from the "Pri_Dep" field of the RMS data set, and are combinations of marriage and dependent status. SNC is coded as '1' if the sailor is single with no children and '0' otherwise;

SWC is coded as '1' if the sailor is single with children and '0' otherwise; MNC and MWC are coded as '1' if the sailor is married without/with children, respectively, and '0' otherwise. Prior studies have found that married persons have a higher propensity to reenlist than those who are single. [Ref. 7, Ref. 20] In 1995, Quester and Adedeji [Ref. 29] further concluded that Marines who were married or had dependents were more likely to reenlist than single Marines with no dependents. Based on these prior findings and the notion that the Navy provides job security and medical benefits to sailors' families, we hypothesize that sailors with dependents, either single or married, will be more likely to reenlist than single sailors with no dependents.

e. Race/Ethnicity

The set of race/ethnicity variables used in this model were created from the race and ethnicity fields of the RMS extract. Hispanics were first separated from the group using the "Ethnic_Group_Actual" field, and the "Race_Actual" field was then used to create the remaining categories. These categories are not designed to allow an individual to be included in more than one group. The variables HISPANIC, BLACK, ASIAN, OTH, and WHITE are coded as '1' if the person is in the respective group and '0' if he or she is not. Based on prior studies that included race/ethnicity in their models [Ref. 7, Ref. 29] and the notion that minorities are likely to have better opportunities in the military versus the civilian sector, the hypotheses for HISPANIC, BLACK, ASIAN, and OTHER are that they will have a positive effect on reenlistment (compared to WHITE).

f. SRB Multiple

A difficulty arose in creating a variable that measures the SRB offered to each sailor. The RMS extract contains a variable from the EMF (Srb_Level) that indicates the SRB level received by individuals who chose to reenlist. To be useful for analysis, the variable needs to indicate what SRB level was offered to all sailors at the decision point regardless of whether or not they accepted the SRB. SRB multiples that are offered can change on a monthly basis, making it difficult to track what SRB level an individual was offered at the decision point. The Center for Naval Analyses provided a data file containing SRB multiples for all zones and all eligible ratings/NECs by month

from 1977 through 2001. [Ref. 31] The RMS extract contains rating information (Pres_Rate_Code_1_4) and up to 10 NECs for each sailor in the data set. The RMS also contains a field that indicates the month and year (tp) of the sailor's EAOS—that is, the month and year when he or she was faced with making a reenlistment decision. This information was used to create the variable SRBM, which is defined as the maximum SRB multiple the individual was offered based on his or her rating and/or NEC during the month and year he or she made the reenlistment decision. The variable created to capture the effects of SRBs on reenlistment in this model is identical to those used in the prior literature. [Ref. 27, Ref. 29] The reenlistment probability is expected to increase as the SRB multiple increases, all else equal.

g. Unemployment

Civilian unemployment rates are often included in retention models to examine the effects of the availability of civilian jobs on the reenlistment decision. The unemployment statistics used in the literature range from Warner and Goldberg's [Ref. 20] use of national rates for specific age groups to Hansen's [Ref. 27] use of unemployment rates in the individual's home state at the decision point. The assumption behind using home state information is that sailors in Zone A may look for prospective jobs in their home areas. However, in this analysis state unemployment information could not be merged with the RMS extract, since the RMS does not contain the EMF field "HOME_OF_RECORD," which indicates an individual's home of record. Having the time period by month and year (tp) for the reenlistment decision did allow monthly national unemployment information to be added to each observation in the data set.

Our hypothesis about the way that unemployment rates reflect the impact of the economy on reenlistment decisions differs somewhat from the literature. We hypothesize that sailors are more likely to notice and react to trends in the economy over time than to the level of the unemployment rate at the exact point in time of their decision. For this reason we created a variable UNEMP_CH12 that measures the change in the national unemployment rate over the 12-month period prior to the decision point. The rates used were monthly, seasonally adjusted, national, civilian unemployment rates for ages 20 and older. The data were obtained from the Bureau of Labor Statistics. [Ref.

32] Reenlistment is expected to be counter-cyclical: that is, reenlistment will decrease with a negative change in unemployment (i.e., when the unemployment trend is downward) and increase with a positive change (i.e., when the unemployment trend is upward).

h. Other Explanatory Variables

The literature supports the use of education and aptitude information in retention models. [Ref. 22] Mehay's survey [Ref. 19] provides specific discussion of these variables, which include high school diploma status, higher education status, and AFQT scores, and these variables have been found to have significant effects on reenlistment decisions. As mentioned previously, including these variables in a model with civilian pay variables could lead to multicollinearity problems. The RMS contains the EMF fields "ED_YRS" and "AFQT_SCORE" variables that could be used to reflect this information, but EMF file managers pointed out that the accuracy of the data in these EMF fields is questionable. [Ref. 33] As a result, these variables were not part of the RMS extract used in this analysis and were not used in the retention model.

3. Model Summary

The final model used in this analysis is generally specified as:

Reenlistment = f (Sea/Shore Duty, Gender, Family Status, Race/Ethnicity, Paygrade, SRB Multiple, Unemployment)

Table 3.1 describes the analysis variables used in the reenlistment model, and the coding of each variable. Table 3.2 provides descriptive statistics for Zone A sailors who made a reenlistment decision during fiscal years 1995 to 2001. For comparison purposes, the sample for these statistics includes sailors in Zone A who extended their enlistments (N=179,316). The average reenlistment rate for this group was 0.466, and the majority of these sailors were single with no children (57.9 percent), white (66.0 percent), in paygrade E-4 (58.6 percent), and male (86.4 percent). Also, 73.3 percent of the sample was at sea at EAOS. The average SRB multiple was 1.36 and the average percentage change in unemployment over the 12 months prior to a reenlistment decision was –0.245. That is, the unemployment rate fell on average by 0.25 percentage points over the 12-month period prior to the reenlistment decision.

Table 3.1. Description of Analysis Variables

Variable	Value	Relationship w/REENL
Dependent Variable		
REENL	=1 if reenlist	
Explanatory Variables		
Sea/Shore Duty		
SEA[b]	=1 if sea duty	- (Compared to SHORE)
SHORE[b]	=1 if shore duty	+ (Compared to SEA)
Gender		
MALE[a]	=1 if male	
FEMALE	=1 if female	+ (Compared to MALE)
Family Status		
SNC[a]	=1 if single, no child	
SWC	=1 if single, w/child	+ (Compared to SNC)
MNC	=1 if married, no child	+ (Compared to SNC)
MWC	=1 if married, w/child	+ (Compared to SNC)
Race/Ethnicity		
WHITE[a]	=1 if White	
HISPANIC	=1 if Hispanic	+ (Compared to WHITE)
BLACK	=1 if Black	+ (Compared to WHITE)
ASIAN	=1 if Asian	+ (Compared to WHITE)
OTH	=1 if Other	+ (Compared to WHITE)
Paygrade		
E3B	=1 if E1-E3	- (Compared to E4 or E5)
E4[b]	=1 if E4	- (Compared to E5)
E5[b]	=1 if E5	+ (Compared to E4)
E6	=1 if E6	+ (Compared to E4 or E5)
SRB Multiple		
SRBM	Max SRB multiple (Range: 0.0 - 8.5)	+
Unemployment		
UNEMP_CH12	12 mo. Unemp. Ch.	+

[a]Base case

[b]Base case if modal value is 1

Table 3.2. Descriptive Statistics of Analysis Variables, FY95-01[a] (N = 179,316).

Variable	Mean	Std Dev
REENL	0.466	0.499
SEA	0.733	0.442
SHORE	0.267	0.442
MALE	0.864	0.343
FEMALE	0.136	0.343
SNC	0.579	0.494
SWC	0.045	0.206
MNC	0.201	0.401
MWC	0.176	0.380
WHITE	0.660	0.474
HISPANIC	0.106	0.308
BLACK	0.175	0.380
ASIAN	0.042	0.201
OTH	0.016	0.126
E3B	0.254	0.435
E4	0.586	0.493
E5	0.158	0.365
E6	0.002	0.046
SRBM (multiple)	1.362	1.788
UNEMP_CH12 (%)	-0.245	0.340

[a]All variables are binary except SRBM and UNEMP_CH12

Table 3.3 provides Zone A reenlistment, extension, and separation rates by analysis variable group for the analysis time period. Reenlistment rates varied from 36.4 percent to 59.5 percent, extension rates from 2.2 to 5.7 percent. A Z-test for the equality of two proportions [Ref. 34] was conducted for each variable group to test for differences in the average reenlistment rates within the group. In the family status, race/ethnicity, and paygrade groups, the rates for SNC, WHITE, and E4, respectively, were tested with the average rates for the rest of the group. For each test the null hypothesis that the reenlistment rates were the same was rejected at the 0.01 significance level. In other words, for sailors in Zone A who made reenlistment decisions from fiscal years 1995 to 2001, a higher proportion of shore duty sailors reenlisted than sea duty sailors (Z = -23.75, *p*-val = 0.000); a higher proportion of men reenlisted than women (Z = 2.77, *p*-val = 0.006); a higher proportion of sailors with dependents reenlisted than sailors with no dependents (Z = 54.82, *p*-val = 0.000); a higher proportion of minorities reenlisted than

Table 3.3. Reenlistment, Extension, and Separation Rates for Analysis Variables FY95-01 (N = 179,316).

Group	Reenl Rate	Ext Rate	Sep Rate
SEA	0.449	0.027	0.524
SHORE	0.512	0.041	0.447
MALE	0.467	0.029	0.504
FEMALE	0.458	0.045	0.497
SNC	0.411	0.030	0.560
SWC	0.527	0.046	0.427
MNC	0.498	0.030	0.472
MWC	0.595	0.034	0.371
WHITE	0.431	0.024	0.545
HISPANIC	0.464	0.033	0.503
BLACK	0.567	0.057	0.377
ASIAN	0.595	0.041	0.364
OTH	0.463	0.028	0.509
E3B	0.364	0.045	0.592
E4	0.500	0.028	0.473
E5	0.504	0.022	0.473
E6	0.468	0.043	0.489

whites (Z = 41.03, p-val = 0.000); and a higher proportion of E-4s reenlisted than sailors in other paygrades (Z = -34.13, p-val = 0.000). These figures are consistent with the hypothesized effect of these variables with the exception of females, who were expected to reenlist at higher rates than men.

Table 3.4 shows the trends in reenlistment, extension, and separation rates for each year contained in the data set. Table 3.4 shows nearly a six percentage point drop in reenlistment rates between fiscal years 1997 and 1999, then a resurgence in reenlistment rates between 2000 and 2001. The reenlistment rate appears to be somewhat higher in 2001 than in any previous year. The trend in the extension rate is slightly downward. The reenlistment rate averaged 46.6 percent, and the extension rate 3.1 percent over this period.

Table 3.4. Zone A Reenlistment, Extension, and Separation Rates by Year.

Fiscal Year	N	Reenl Rate	Ext Rate	Sep Rate
1995	25,982	0.482	0.042	0.476
1996	23,478	0.474	0.037	0.489
1997	28,519	0.417	0.034	0.549
1998	25,241	0.424	0.032	0.544
1999	24,077	0.414	0.028	0.559
2000	24,613	0.472	0.024	0.504
2001	27,406	0.572	0.021	0.407
Total	179,316	0.466	0.031	0.503

D. STATISTICAL MODEL

The dependent variable used in this model depicts a choice to either reenlist or leave the Navy. A model is needed that best represents this type of behavior, since the outcomes of this decision are binary. The cumulative logistic funcion is a functional relationship between a binary decision outcome, D_i, and a set of explanatory variables and can be modeled as:

$$P_i = \frac{1}{1+e^{-Z_i}}$$

or

$$\ln\left(\frac{P_i}{1-P_i}\right) = Z_i = \beta_0 + \beta_1 X_{1i} + \cdots + \beta_k X_{ki}$$

where P_i is the probability that individual i chooses to reenlist ($D_i = 1$) given the k independent variables (X_i) in the model, and Zi is the cumulative logistic function. If a linear probability model (LPM) is used to model this type of behavior, the resulting coefficients may produce estimates for Di that are outside the meaningful range of values [1,0]. The characteristic S-shape curve of the logit is used often to represent behavioral decision models and does not have the same problem with unboundedness that the simpler LPM has with a binary dependent variable. [Ref. 35] Figure 3.1 provides a visual comparison of the LPM and logit models.

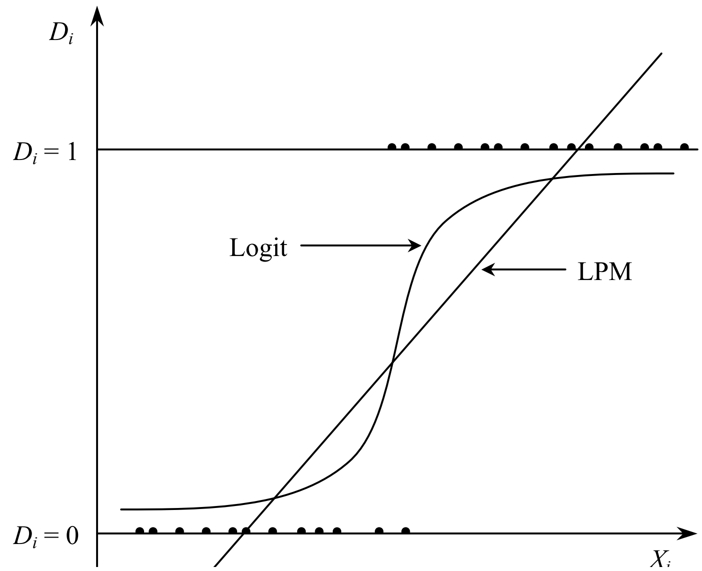

Figure 3.1. Logit – LPM Comparison. [After Ref. 35: Fig. 13.2].

The estimated coefficients (β_k) from this logistic equation describe the change in the log of the odds of reenlisting caused by a one-unit change in the respective independent variables, holding the other variables constant. Since this does not provide any specific insight as to how an individual's behavior is affected by each variable, the partial effects of each characteristic on the reenlistment decisions of a reference "base case" or "notional" person must be computed. By changing the value of each variable from its "notional" value, one can examine the marginal (or partial) effect of the explanatory variable on reenlistment. The partial effect measures the change in the probability of reenlistment for a one-unit change in the respective independent variable. If the explanatory variable is binary, the partial effect measures the impact of going from zero to one.

The estimates of a logit model can be tested for overall "goodness-of-fit" by using the –2 Log Likelihood statistic. This statistic has a chi-square distribution under the null hypothesis that all of the explanatory variables in the model have coefficients of zero. [Ref. 36] The resulting score has an associated probability, or p-value, of obtaining that score or higher given that the null hypothesis is true. Generally, if this p-value is less than 0.1, the statistic is considered significant, and the null hypothesis can be rejected. Rejecting the null hypothesis in this case indicates that the model has some explanatory power. Researchers often use the percentage of correct classifications as another goodness-of-fit measure for logit models. This metric is based on a cutoff percentage

value for P_i used to determine what estimates for D_i are classified as '1' or '0'. If, for example, the cutoff for P_i were 0.5, then D_i would be '1' for values of P_i greater than or equal to 0.5, and D_i would be '0' for values of P_i less than 0.5. The percent correctly classified would be the ratio of the number of observations that were correctly classified to the total number of observations in the sample.

The actual specification of the logit model in this thesis is:

$$\ln\left(\frac{P_i}{1\text{-}P_i}\right) = \beta_0+b_1(\text{SEA})+\beta_2(\text{FEMALE})+\beta_3(\text{SWC})+\beta_4(\text{MNC})+\beta_5(\text{MWC})+ \beta_6(\text{HISPANIC})+\beta_7(\text{BLACK})+\beta_8(\text{ASIAN})+\beta_9(\text{OTH})+\beta_{10}(\text{E3B})+ \beta_{11}(\text{E5})+\beta_{12}(\text{E6})+\beta_{13}(\text{SRBM})+\beta_{14}(\text{UNEMP\_CH12})$$

where P_i is the probability of reenlistment and the explanatory variables are defined in Table 3.1. The results of estimating this model are discussed in Chapter IV.

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IV. DATA ANALYSIS

A. INTRODUCTION

This chapter analyzes the results of applying the theoretical model developed and specified in Chapter III to the analysis data set. The data used were extracted from the RMS with the intent to examine the strengths and weaknesses of the current PerSMART structure in supporting retention modeling. The analysis data set includes only sailors in SRB Zone A who made a decision to reenlist or separate during fiscal years 1995 through 2001, and the focus of the analysis is on the effects of SRBs on reenlistment

B. MODEL GROUPS

The data set extracted from the RMS provides excellent analysis opportunities, since the Zone-A grouping alone contains actual reenlistment data for more than 90 different enlisted ratings. Modeling each rating individually would not be practical or possible, as few of the ratings by themselves have sufficient observations to support reliable maximum likelihood estimation. In order to make use of as much of the data set as possible, the ratings need to be grouped in some logical fashion to provide for more reliable parameter estimates. Warner and Goldberg in their 1984 study [Ref. 20] grouped all Navy ratings into 16 Navy occupational areas based on similarities in training, job requirements, and working conditions. The groups they used are similar to the Enlisted Management Communities (EMC) that the Navy's Military Personnel Plans and Policy Division (N13) currently uses to manage enlisted personnel programs. [Ref. 37] Table 4.1 shows the ratings and/or NECs associated with each EMC.

The Enlisted Management Community organization is the basis for which the Navy ratings were grouped in this analysis. The ratings in these communities all have similar jobs, skills and sea-shore rotations. The 173,735 sailors who reenlisted or separated in Zone A between fiscal years 1995 and 2001 were assigned to groups according to the ratings and/or NECs in Table 4.1. Table 4.1 includes the name of the community (e.g., Aviation Mechanical) in column 1, the variable name (AVMECH) in column 2, and the list of ratings/NECs contained in each occupational grouping in column 3.

Table 4.1. Enlisted Management Communities

Community	Abbrev	Rating/NEC
Aviation Mechanical	AVMECH	AB ABE ABH ABF AD AF AM AME AMH AMS AO AS PR
Aviation Technical/Aircrew	AVTECH	AC AE AG AT AV AW AZ
Surface Main Propulsion	SMPROP	GS GSM GSE EN MM *BT*
Surface Hull/Electrical	SHELEC	DC HT EM IC MR
Surface Combat Systems	SCSYS	ET FC GM MN STG TM
Surface Operations	SOPER	BM IT OS QM SM *RM DP DS*
SpecWar/EOD/Diver	SPEC	Any Rating Except HM w/NECs 5332 5333 5334 5335 5336 5337 5320 5323 5326 5311 5341 5342 5343 5346 5350 5351 5352
Cryptologic/Foreign Lang	CRYPTO	CTA CTI CTM CTO CTR CTT EW
Submarine Personnel	SUB	ET(SS) FT MM(SS) MS(SS) MT SK(SS) STS YN(SS)
NUC	NUC	ET EM MM w/Nuclear NECs 3353 3354 3355 3356 3359 3363 3364 3365 3366 3383 3384 3385 3386 3389 3393 3394 3395 3396
Admin/Media	ADMIN	DM JO PN PH RP YN
Medical/Dental	HEALTH	HM DT (HN DN)
Legal/Law Enforcement	LAW	LN MA NC NCCR
Supply	SUPPLY	AK DK LI MS PC SH SK
Seabees	SEABEE	BU CE CM CU EA DO EQ SW UC UT CN
Intel Specialist	INTEL	IS

Note: Ratings in italics existed during the time period for this data set, but have since been merged into other ratings in the same community.
Source:[Ref. 4.2]

In the downsizing period many ratings were either merged into a single rating or closed completely. An example of this is the Boiler Technician (BT) rating that was merged with the Machinist Mate (MM) rating. Some of the now obsolete ratings, such as Patternmaker (PM) and Opticalman (OM), could not be assigned to a current community and were dropped from the analysis. Additionally, sailors with no rating in paygrades E-1 through E-3 (nonrates) were not assigned to any group, since they were not eligible for an SRB and are not managed in the same manner as sailors with ratings. Nonrates include Airman (AN), Seaman (SN) and Fireman (FN). Three of the 16 communities--

SpecWar/EOD/Diver, Legal/Law enforcement, and Intel Specialist-- were not used in this analysis because of the small sample sizes of each. After deleting non-rates and the 'Specwar, Legal, and Intel' groupings, the final analysis data set contained 151,554 observations in 13 separate rating groups.

Table 4.2 provides descriptive statistics of the analysis variables by Enlisted Management Community. The Submarine personnel community had the highest reenlistment rate (0.636), while the Surface Hull/Electrical community had the lowest rate (0.382). All but two communities, Cryptologic/Foreign Language and Health, had more sailors on sea duty than on shore duty. This is as expected since CTs are typically assigned to shore-based communications facilities, and HMs/DTs are primarily assigned to Naval hospitals and dental clinics. The Health community had the highest proportion of women (0.301), while Surface Combat Systems had the lowest (0.063) (excluding the Submarine and Nuclear communities, since women cannot serve on submarines). Health had a greater proportion of married sailors (0.492) than other communities, and Surface Operations had the greatest proportion of single sailors (0.675).

In all communities the majority of sailors were white single men with no children. Minority groups constituted the majority in the Supply community (0.535); the proportions of minority groups in Supply were: Hispanics (0.12), Blacks (.305), and Asians (0.097). The Nuclear community had the largest proportion of petty officers (E-4 through E-6) (0.994). This is to be expected since nuclear trained sailors leave their initial schools as petty officers. The 12-month unemployment rate for all communities was decreasing with the largest decrease for the Health community (-0.272 percentage points) and the smallest for the Surface Combat Systems community (-0.193 percentage points).

Table 4.3 shows the percentage of each community eligible to receive an SRB during the time period (i.e., SRBM > 0.0). Relatively few sailors in the Surface Hull/Electrical, Admin/Media, Health, and Supply communities were eligible for SRBs during fiscal years 1995-2001.

Table 4.2. Descriptive Statistics of Analysis Variables by Enlisted Management Community, FY95-01[a].

	AVMECH		AVTECH		SMPROP		SHELEC		SCSYS		SOPER		CRYPTO	
Sample Size	20,770		15,489		12,924		11,813		14,255		18,312		5,988	
Variable	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
REENL	0.448	0.497	0.473	0.499	0.456	0.498	0.382	0.486	0.590	0.492	0.487	0.500	0.582	0.493
SEA	0.796	0.403	0.719	0.450	0.836	0.370	0.803	0.398	0.779	0.415	0.838	0.368	0.415	0.493
SHORE	0.204	0.403	0.281	0.450	0.164	0.370	0.197	0.398	0.221	0.415	0.162	0.368	0.585	0.493
MALE	0.917	0.276	0.883	0.322	0.931	0.254	0.918	0.275	0.937	0.242	0.874	0.332	0.770	0.421
FEMALE	0.083	0.276	0.117	0.322	0.069	0.254	0.082	0.275	0.063	0.242	0.126	0.332	0.230	0.421
SNC	0.577	0.494	0.554	0.497	0.599	0.490	0.591	0.492	0.559	0.497	0.626	0.484	0.575	0.494
SWC	0.041	0.198	0.040	0.196	0.039	0.193	0.040	0.195	0.028	0.166	0.049	0.217	0.039	0.194
MNC	0.205	0.404	0.219	0.414	0.179	0.383	0.195	0.396	0.216	0.411	0.173	0.378	0.224	0.417
MWC	0.178	0.382	0.187	0.390	0.183	0.387	0.174	0.380	0.197	0.398	0.152	0.359	0.161	0.368
WHITE	0.677	0.468	0.737	0.441	0.611	0.488	0.689	0.463	0.776	0.417	0.625	0.484	0.769	0.421
HISPANIC	0.122	0.327	0.102	0.303	0.121	0.326	0.105	0.306	0.083	0.276	0.101	0.301	0.069	0.254
BLACK	0.136	0.343	0.124	0.330	0.178	0.382	0.147	0.354	0.100	0.300	0.235	0.424	0.133	0.339
ASIAN	0.047	0.211	0.023	0.149	0.071	0.256	0.042	0.200	0.024	0.152	0.025	0.156	0.013	0.112
OTH	0.018	0.135	0.014	0.118	0.020	0.141	0.018	0.132	0.017	0.130	0.015	0.121	0.016	0.126
E3B	0.292	0.455	0.159	0.366	0.092	0.289	0.109	0.312	0.039	0.193	0.106	0.307	0.100	0.299
E4	0.639	0.480	0.629	0.483	0.781	0.413	0.714	0.452	0.639	0.480	0.713	0.452	0.585	0.493
E5	0.069	0.254	0.211	0.408	0.125	0.331	0.176	0.381	0.322	0.467	0.181	0.385	0.314	0.464
E6	0.000	0.010	0.000	0.014	0.002	0.042	0.001	0.028	0.001	0.025	0.000	0.018	0.001	0.029
SRBM	1.015	1.164	1.892	1.218	1.219	0.964	0.336	0.664	2.633	2.017	1.682	1.333	2.614	1.636
UNEMP_CH12	-0.220	0.343	-0.233	0.344	-0.241	0.356	-0.264	0.355	-0.193	0.369	-0.252	0.345	-0.217	0.343

[a]All variables are binary except SRBM and UNEMP_CH12.

Table 4.2. (Continued)[a]

	SUB		NUC		ADMIN		HEALTH		SUPPLY		SEABEE	
Sample Size	7,640		7,465		7,328		13,415		11,914		4,241	
Variable	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
REENL	0.636	0.481	0.483	0.500	0.544	0.498	0.501	0.500	0.523	0.499	0.569	0.495
SEA	0.960	0.195	0.864	0.342	0.526	0.499	0.292	0.455	0.768	0.422	0.855	0.352
SHORE	0.040	0.195	0.136	0.342	0.474	0.499	0.708	0.455	0.232	0.422	0.145	0.352
MALE	1.000	0.000	0.983	0.128	0.716	0.451	0.699	0.459	0.773	0.419	0.925	0.263
FEMALE	0.000	0.000	0.017	0.128	0.284	0.451	0.301	0.459	0.227	0.419	0.075	0.263
SNC	0.565	0.496	0.615	0.487	0.495	0.500	0.456	0.498	0.548	0.498	0.557	0.497
SWC	0.026	0.159	0.010	0.102	0.067	0.249	0.052	0.222	0.068	0.252	0.042	0.200
MNC	0.221	0.415	0.231	0.422	0.229	0.420	0.270	0.444	0.189	0.392	0.191	0.393
MWC	0.189	0.391	0.143	0.350	0.209	0.407	0.222	0.415	0.194	0.396	0.211	0.408
WHITE	0.783	0.412	0.878	0.327	0.548	0.498	0.658	0.474	0.465	0.499	0.735	0.441
HISPANIC	0.088	0.283	0.058	0.233	0.119	0.324	0.115	0.319	0.120	0.324	0.108	0.310
BLACK	0.093	0.290	0.030	0.171	0.271	0.444	0.146	0.353	0.305	0.460	0.104	0.305
ASIAN	0.018	0.132	0.023	0.150	0.046	0.209	0.070	0.254	0.097	0.296	0.036	0.186
OTH	0.019	0.136	0.011	0.105	0.017	0.131	0.012	0.108	0.014	0.118	0.017	0.130
E3B	0.088	0.284	0.006	0.078	0.159	0.366	0.321	0.467	0.284	0.451	0.230	0.421
E4	0.739	0.439	0.468	0.499	0.687	0.464	0.635	0.482	0.625	0.484	0.594	0.491
E5	0.172	0.377	0.499	0.500	0.153	0.360	0.044	0.205	0.091	0.288	0.175	0.380
E6	0.001	0.028	0.027	0.163	0.000	0.017	0.000	0.015	0.000	0.013	0.001	0.027
SRBM	3.619	1.799	5.691	1.648	0.020	0.295	0.374	0.865	0.125	0.355	0.698	0.651
UNEMP_CH12	-0.198	0.335	-0.269	0.324	-0.271	0.323	-0.272	0.326	-0.253	0.326	-0.204	0.363

[a]All variables are binary except SRBM and UNEMP_CH12.

Table 4.3. Percentage of Sailors Eligible For SRB by Enlisted Management Community, Fiscal Years 1995-2001.

EMC	N	Percent Eligible
AVMECH	20,770	56.80
AVTECH	15,489	80.39
SMPROP	12,924	74.14
SHELEC	11,813	34.23
SCSYS	14,255	72.20
SOPER	18,312	73.01
CRYPTO	5,988	85.35
SUB	7,640	96.83
NUC	7,465	100.00
ADMIN	7,328	0.52
HEALTH	13,415	19.62
SUPPLY	11,914	15.50
SEABEE	4,241	60.46

Table 4.4 shows the average SRB multiple for each community by fiscal year. The SUB and NUC communities had the highest average SRB award levels during this period, while Admin, Health, and Supply had the lowest.

Table 4.4. Average SRB multiples by Enlisted Management Community.

EMC	FY95	FY96	FY97	FY98	FY99	FY00	FY01
AVMECH	0.40	0.12	0.42	0.63	1.25	1.72	2.08
AVTECH	1.19	1.50	1.73	1.77	1.95	2.28	2.62
SMPROP	0.57	0.78	0.92	1.42	1.56	1.61	1.69
SHELEC	0.49	0.49	0.12	0.03	0.18	0.38	0.60
SCSYS	0.69	1.67	2.63	2.64	2.85	3.60	3.77
SOPER	1.52	1.45	1.01	1.65	2.13	2.10	2.00
CRYPTO	0.95	2.11	2.64	2.43	2.86	3.28	3.60
SUB	1.97	2.48	2.56	2.49	4.07	5.01	4.96
NUC	4.08	4.05	4.66	5.43	7.22	7.43	6.96
ADMIN	0.00	0.00	0.01	0.04	0.05	0.04	0.00
HEALTH	0.35	0.35	0.35	0.34	0.43	0.39	0.41
SUPPLY	0.21	0.00	0.00	0.01	0.19	0.22	0.28
SEABEE	0.09	0.63	0.67	0.43	0.63	1.01	1.08

C. MODEL ANALYSIS

The reenlistment model specified in Chapter III was estimated for each of the 13 selected Enlisted Management Community groups. The estimating equations are nonlinear and are estimated by maximum likelihood techniques using the SAS statistical software package. Estimated coefficients indicate the magnitude and direction of the statistical relationship between the explanatory variables and the log-odds of reenlisting.

As mentioned in Chapter III, the estimated coefficients from the logit model describe the change in the log of the odds of reenlisting associated with a change in a given explanatory variable, holding the other variables constant. Since this does not provide any specific insight as to how an individual's behavior is affected by each variable, the partial effects of each characteristic on the reenlistment decisions of a reference or "notional" person must be computed. Because the functional form of the logit equation is nonlinear, the value of the partial effects depends on where the logit model is evaluated. The "notional" sailor used in this analysis for evaluating partial effects has characteristics matching the modal value for categorical variables and the mean value for continuous variables. For example, the "notional" sailor for the Health community was a single white male E-4 on shore duty. His SRB multiple was at the mean of the community (0.374), and he saw a 0.253 percentage point decrease in unemployment over the 12 months prior to his reenlistment decision. The partial effects of explanatory variables on this "notional" sailor's probability of reenlisting are evaluated by changing binary variables from '0' to '1,' increasing his SRB multiple by one level to 1.374, and decreasing the magnitude of the unemployment rate change by 0.2 percentage points to –0.053.

Table 4.5 presents the logit coefficients for each of the 13 community models. Table 4.4 also shows the partial effect for each coefficient. The specification for all models is the same except where SHORE was used as the comparison group in the Cryptologic/Foreign Language and Medical/Dental communities, and E5 was used as the comparison group in the Nuclear community. In general, the estimates reveal that higher SRB multiples and rising unemployment rates are associated with higher probabilities for reenlisting. Also, minorities with dependents are more likely to reenlist than whites

Table 4.5. Logit Estimates of Reenlistment Models.

	AVMECH		AVTECH		SMPROP		SHELEC		SCSYS		SOPER		CRYPTO	
Variable	Coeff.	Partial Effect	Coeff.	Partial Effect	Coeff.	Partial Effect	Coeff.	Partial Effect	Coeff.	Partial Effect	Coeff.	Partial Effect	Coeff.	Partial Effect
Intercept	-0.835 [a]	---	-0.649 [a]	---	-0.910 [a]	---	-1.136 [a]	---	-0.424 [a]	---	-0.737 [a]	---	-0.001	---
SHORE	0.087 [b]	0.020	0.120 [a]	0.029	1.253 [a]	0.300	1.102 [a]	0.247	0.788 [a]	0.183	0.025	0.006	---	---
SEA	---	---	---	---	---	---	---	---	---	---	---	---	-0.118 [b]	-0.029
FEMALE	-0.172 [a]	-0.038	-0.205 [a]	-0.047	-0.283 [a]	-0.056	-0.203 [a]	-0.035	-0.081	-0.020	-0.058	-0.013	0.027	0.007
SWC	0.398 [a]	0.095	0.415 [a]	0.101	0.293 [a]	0.065	0.379 [a]	0.075	0.398 [a]	0.097	0.541 [a]	0.131	0.546 [a]	0.132
MNC	0.433 [a]	0.104	0.321 [a]	0.078	0.464 [a]	0.105	0.335 [a]	0.066	0.333 [a]	0.081	0.436 [a]	0.105	0.277 [a]	0.068
MWC	0.798 [a]	0.194	0.737 [a]	0.181	0.711 [a]	0.165	0.708 [a]	0.150	0.767 [a]	0.178	0.852 [a]	0.208	0.707 [a]	0.167
HISPANIC	0.332 [a]	0.079	0.288 [a]	0.070	0.186 [a]	0.040	0.301 [a]	0.059	0.171 [a]	0.042	0.167 [a]	0.039	0.139	0.035
BLACK	0.855 [a]	0.209	0.827 [a]	0.203	0.839 [a]	0.197	1.029 [a]	0.229	0.841 [a]	0.194	1.014 [a]	0.248	0.609 [a]	0.146
ASIAN	0.971 [a]	0.237	0.190 [c]	0.045	0.860 [a]	0.203	1.129 [a]	0.253	0.679 [a]	0.160	0.644 [a]	0.157	0.158	0.039
OTH	0.136	0.032	0.102	0.024	0.204	0.044	0.268 [c]	0.052	0.187	0.046	0.018	0.004	-0.051	-0.013
E3B	-0.335 [a]	-0.072	-0.150 [a]	-0.034	-0.321 [a]	-0.062	-0.755 [a]	-0.110	-0.456 [a]	-0.113	-0.087 [c]	-0.020	0.404 [a]	0.099
E4	---	---	---	---	---	---	---	---	---	---	---	---	---	---
E5	0.672 [a]	0.163	0.247 [a]	0.059	0.467 [a]	0.106	0.426 [a]	0.086	-0.628 [a]	-0.154	0.296 [a]	0.070	-0.060	-0.015
E6	9.863	0.651	0.706	0.174	0.824 [c]	0.194	0.955	0.210	-0.866	-0.208	1.394	0.334	0.141	0.035
SRBM	0.217 [a]	0.051	0.084 [a]	0.020	0.114 [a]	0.024	0.202 [a]	0.039	0.235 [a]	0.058	0.091 [a]	0.021	0.034 [c]	0.008
UNEMP_CH12	0.037	0.002	0.086 [c]	0.004	0.377 [a]	0.016	0.349 [a]	0.013	0.408 [a]	0.020	0.032	0.001	0.037	0.002
Sample Size	20,770		15,489		12,924		11,813		14,255		18,312		5,988	
Model Chisq	1696.1		700.5		1347.6		1306.7		1634.2		1405.5		197.2	
Percent Correct[d]	62.6		58.9		64.6		67.2		65.6		62.0		59.6	
Predicted Reenl. Rate*		0.349		0.375		0.297		0.239		0.529		0.356		0.520

Note: Partial Effects evaluated by individually changing categorical variables from their modal values, increasing SRBM by 1 level, and decreasing the magnitude of UNEMP_CH12 by 0.2 percentage points.

*Predicted reenlistment probability for "notional" person in sample.

[a] $p<0.01$

[b] $p<0.05$

[c] $p<0.10$

[d] Predictions at 0.5 cutoff value for P.

Table 4.5. (Continued)

	SUB		NUC		ADMIN		HEALTH		SUPPLY		SEABEE	
Variable	Coeff.	Partial Effect	Coeff.	Partial Effect	Coeff.	Partial Effect	Coeff.	Partial Effect	Coeff.	Partial Effect	Coeff.	Partial Effect
Intercept	-0.132 [c]	---	-2.012 [a]	---	-0.106 [b]	---	-0.278 [a]	---	-0.382 [a]	---	-0.501 [a]	---
SHORE	-0.262 [b]	-0.065	1.671 [a]	0.345	-0.359 [a]	-0.088	---	---	-0.380 [a]	-0.088	-0.065	-0.016
SEA	---	---	---	---	---	---	-0.182 [a]	-0.044	---	---	---	---
FEMALE	---	---	1.379 [a]	0.273	-0.089	-0.022	-0.213 [a]	-0.051	-0.151 [a]	-0.036	-0.187	-0.046
SWC	0.603 [a]	0.142	0.232	0.034	0.421 [a]	0.105	0.357 [a]	0.089	0.400 [a]	0.099	0.278	0.069
MNC	0.662 [a]	0.155	0.345 [a]	0.053	0.232 [a]	0.058	0.176 [a]	0.044	0.373 [a]	0.092	0.377 [a]	0.094
MWC	1.137 [a]	0.246	1.136 [a]	0.214	0.642 [a]	0.158	0.630 [a]	0.156	0.543 [a]	0.135	0.655 [a]	0.161
HISPANIC	0.033	0.008	-0.214 [c]	-0.027	0.231 [a]	0.058	0.238 [a]	0.059	0.364 [a]	0.090	0.737 [a]	0.180
BLACK	0.775 [a]	0.178	0.311 [c]	0.047	0.852 [a]	0.205	0.735 [a]	0.181	0.853 [a]	0.210	1.195 [a]	0.278
ASIAN	0.293	0.072	-0.174	-0.022	0.862 [a]	0.207	0.968 [a]	0.235	1.235 [a]	0.295	1.391 [a]	0.314
OTH	0.314	0.076	0.517 [c]	0.083	-0.067	-0.017	0.201	0.050	0.153	0.038	0.582 [b]	0.144
E3B	0.442 [a]	0.106	1.270 [a]	0.246	-0.370 [a]	-0.090	-0.127 [a]	-0.031	-0.432 [a]	-0.099	-0.138 [c]	-0.034
E4	---	---	2.353 [a]	0.509	---	---	---	---	---	---	---	---
E5	-0.245 [a]	-0.061	---	---	0.413 [a]	0.103	0.695 [a]	0.172	0.951 [a]	0.233	0.244 [a]	0.061
E6	1.066	0.233	0.264	0.039	-0.230	-0.057	11.025	0.568	0.502	0.124	-1.115	-0.242
SRBM	0.104 [a]	0.026	0.070 [a]	0.010	0.016	0.004	-0.007	-0.002	0.068	0.017	0.418 [a]	0.104
UNEMP_CH12	0.439 [a]	0.022	0.100	0.003	0.075	0.004	-0.028	-0.001	-0.053	-0.003	-0.265 [a]	-0.013
Sample Size	7,640		7,465		7,328		13,415		11,914		4,241	
Model Chisq	543.9		2786.9		496.4		676.7		1132.7		343.5	
Percent Correct[d]	65.9		76.2		60.7		59.5		62.4		62.8	
Predicted Reenl. Rate*		0.540		0.163		0.469		0.432		0.411		0.461

Note: Partial Effects evaluated by individually changing categorical variables from their modal values, increasing SRBM by 1 level, and decreasing the magnitude of UNEMP_CH12 by 0.2 percentage points.

*Predicted reenlistment probability for "notional" person in sample.

[a] $p<0.01$

[b] $p<0.05$

[c] $p<0.10$

[d] Predictions at 0.5 cutoff value for P.

without dependents. Evaluation of the models and a fuller discussion of the results are provided below.

1. Goodness-of-Fit

An ultimate goal in developing a behavioral model should be specifying explanatory variables that are theoretically sound and relevant to the problem being analyzed. Prior literature indicates that the variables used in these models are theoretically important factors in estimating the probability of reenlistment. In all but one of the 13 community models, the majority of variables are statistically significant.

All of the models had a high chi-square score that tests the null hypothesis that all of the explanatory variables in the model have coefficients of zero. In all cases this null hypothesis was rejected at the 0.01 significance level, indicating that all of the models had some explanatory power. The percentage of correct classifications was examined for each model at a cutoff value of 0.5 and results ranged from a low of 58.9 percent in the Aviation Technical community model to a high of 76.2 percent of correct classifications in the Nuclear community model. These figures can be compared to the "naïve" prediction rule that assumes everyone follows the majority (i.e., everyone would separate if the majority of sailors in the community actually separated). For example, the majority of sailors in the Surface Main Propulsion community separated (54.4 percent). The "naïve" prediction for this community would be that all sailors will separate, and it would correctly classify 54.4 percent of the predictions. The actual logistic model for the SMPROP community correctly predicted 64.6 percent of the cases. Comparing the two predictions shows that the model performs better than the "naïve" prediction. This same comparison was made for each logit model, and all logit models were found to predict better than the prediction based on a "naïve" approach.

All explanatory variables were examined for correlation, and an ordinary least squares regression was performed on this model to examine any multicollinearity conditions between the explanatory variables. The variables FEMALE and SEA/SHORE were significantly correlated ($0.31 < |r| < 0.40$) in the Surface Operations, Cryptologic/Foreign Language, Admin/Media, Medical/Dental, and Supply community models. The SRB and unemployment variables showed similar correlation ($0.30 < |r| <$

0.40) in seven of the models. The variance inflation factors (VIF) for the models in these cases were higher for the variables as well, indicating possible multicollinearity in the affected models. This is not considered a serious problem, however, as multicollinearity affects the standard errors of parameter estimates, but the parameters themselves remain unbiased.

2. Effects of Explanatory Variables

a. Sea/Shore Duty

Sea and shore duty have a significant effect on reenlistment in 11 of the 13 communities. Eight of the models support the hypothesized negative effect of current sea duty on retention. That is, in eight models those currently (at EAOS) on sea duty are less likely to reenlist than those currently on shore duty. A surprising finding, however, is that shore duty has a negative effect on reenlistment in three of the communities: Submarine Personnel, Admin/Media, and Supply. That is, those currently on shore duty who face going to sea are less likely to reenlist than those on sea duty. The results from these three models indicate that sailors in these communities either prefer sea duty and dislike shore duty, or that the prospect of sea duty reduces their likelihood of reenlisting. The latter is likely to be more correct and would support Warner and Goldberg's [Ref. 20] use of a prospective sea duty variable. Of the significant estimates, shore duty has an average effect of +8.5 percentage points on "notional" reenlistment rates (or that sea duty decreases the likelihood of reenlisting by 8.5 percentage points). Warner and Goldberg found that a 10 percent increase in the fraction of expected time at sea reduces reenlistment rates by only 1.6 percentage points. The implication of the highly negative effects of sea duty in this analysis are that SRBs would have to increase reenlistment rates by more than 8.5 percentage points in sea duty assignments.

b. Gender

Gender is one of the less important explanatory variables across the models; FEMALE is significant in only seven of the 13 models. Three of the communities where gender is not significant (Surface Operations, Cryptologic/Foreign Language, Admin/Media) have a high correlation between females and shore duty. Females were less likely to reenlist than males in six of the seven models that had

significant coefficients, and this is supported by the significantly lower reenlistment rates for women during this time period. The Nuclear community shows a drastic difference in the effects of gender than the other communities. Women in the Nuclear community with "notional" characteristics are 27.3 percentage points more likely to reenlist than males, although the proportion of women in this community (1.7 percent) is much lower than in other communities.

c. Family Status

All of the family status variables were very consistent across the communities. SWC, MNC, and MWC all show a positive effect on reenlistment rates. The average partial effects on reenlistment rates over the "notional" predicted values across significant models are 10.3, 8.4, and 17.8 percentage point increases, respectively, for sailors who are single with children, married without children, and married with children. These values, however, may be biased due to the naïve variables used to capture the effects of military pay in this model. Since the paygrade variables used in the models do not completely account for all aspects of military pay, the coefficients of the family status variables probably absorb much of the effects of additional fringe benefits accruing to sailors with dependents.

d. Race/Ethnicity

The set of race and ethnicity variables indicates significantly higher reenlistment rates for Hispanics, Blacks, and Asians as compared to Caucasians. The variable for "other" races is significant in only three of the models. This is likely due to the small number of sailors in this category for all communities. Averages of the significant partial effects for Hispanics, Blacks, and Asians indicate that they are 6.3, 19.4, and 21.1 percentage points, respectively, more likely to reenlist than "notional" white sailors.

e. Paygrade

The set of paygrade variables shows that, for most communities, sailors in paygrades E-3 and below behave as expected and have lower reenlistment probabilities than "notional" E-4's. The exceptions to this are in the Cryptologic/Foreign Language, Submarine Personnel, and Nuclear communities. Here those in grades E1-E3 are more

likely to reenlist than sailors in higher paygrades. The variable for E-5s is significant in 11 of the groups where it was compared to E-4s, and the coefficient is generally positive. However, two of the communities (Surface Combat Systems, Submarine Personnel) show lower reenlistment rates for E-5s compared to "notional" E-4s. The Nuclear community has the most dramatic differences from expectations with E-3s and E-4s having 24.6 and 50.9 percent higher probabilities of reenlisting, respectively, than "notional" E-5s. The variable for the E-6 paygrade is significant in only one of the models. Descriptive statistics show that there are few observations in this category across all of the communities. Unfortunately, this naïve use of paygrade variables as proxies for military pay does not capture the full effects of pay on reenlistment as would a more sophisticated civilian-military pay ratio ACOL variable.

f. SRB Multiple

The estimated coefficient of the SRB multiple variable is significant in all but three of the 13 models. As Table 4.4 depicts, very few sailors in the Admin/Media, Medical/Dental, and Supply communities are ever eligible for any level of SRB, and this is likely the reason that SRBs have no effect on reenlistment in these groups. The partial effects of a one-level SRB increase on the "notional" reenlistment rate for the community range from +0.8 percentage points in the Cryptologic/Foreign Language community to +10.4 percentage points in the Seabee community. The average increase in reenlistment probabilities due to a one-level increase in SRB multiples across all significant models is 3.6 percentage points. This effect is consistent with Warner and Goldberg [Ref. 20] who found an average 3.2 percentage point increase across 15 of their occupational groups. Table 4.6 shows the predicted probabilities for reenlistment in each community with different SRB multiples.

A difference between the Warner and Goldberg study and this analysis is that their study used an ACOL variable. To estimate the effects of a one-level increase in the SRB multiple, they increased the military pay portion of the ACOL variable by an equivalent monetary value. Another difference with their study is that the lowest average SRB multiple of any of their occupational groups was 1.1, and the highest was just 4.2.

Table 4.6. Predicted Probabilities for Reenlistment for Each EMC by SRB Multiple.

EMC	0.0	1.0	2.0	3.0	4.0	5.0	6.0	7.0	8.0
AVMECH	0.301	0.348	0.399	0.452	0.506	0.560	0.612	0.662	0.709
AVTECH	0.339	0.358	0.377	0.397	0.418	0.438	0.459	0.480	0.500
SMPROP	0.270	0.293	0.318	0.343	0.369	0.396	0.423	0.451	0.480
SHELEC	0.229	0.267	0.308	0.353	0.401	0.450	0.500	0.550	0.600
SCSYS	0.374	0.431	0.489	0.547	0.605	0.659	0.710	0.756	0.796
SOPER	0.322	0.342	0.363	0.385	0.407	0.429	0.451	0.474	0.497
CRYPTO	0.498	0.506	0.515	0.523	0.531	0.540	0.548	0.556	0.565
SUB	0.443	0.469	0.495	0.521	0.547	0.572	0.598	0.622	0.647
NUC	0.116	0.123	0.130	0.139	0.148	0.157	0.166	0.176	0.187
ADMIN	0.469	0.473	0.477	0.481	0.485	0.489	0.494	0.498	0.501
HEALTH	0.432	0.430	0.429	0.427	0.425	0.424	0.423	0.421	0.419
SUPPLY	0.409	0.425	0.442	0.459	0.477	0.492	0.510	0.527	0.544
SEABEE	0.391	0.494	0.597	0.692	0.773	0.838	0.887	0.922	0.948

There is a much larger variation in SRB multiples with the groups in the data used in this thesis.

Comparing Table 4.4 with the partial effects of SRBM in the different models, it appears there may be some correlation over time between the size of the estimated effect and the consistency of the SRB multiples. Communities that experienced large increases in their average SRB multiples over the time period (i.e., Surface Combat Systems, and Seabee) also have large partial effects for the SRB multiples. Similarly, communities that have consistently higher SRB multiples over the time period show smaller effects on reenlistment by SRB multiples. Nuclear sailors always have a relatively high SRB multiple, and all of them receive a bonus if they reenlist. Since all of them can receive a bonus there is little variation in the SRB multiples within the community.

For additional analysis, all models were estimated by fiscal year to examine any trends in the partial effects of SRBs on reenlistment. Table 4.7 shows the results of this analysis. As Table 4.7 shows, in many years the coefficients of SRBM are insignificant. Often this is due to small sample sizes for each fiscal year – EMC cell. No discernable trends were found to exist, but the results emphasize the value of aggregating data on reenlistment decisions over time to increase sample size and variation in the explanatory variables.

Table 4.7. Partial Effects of SRBM on Reenlistment by Fiscal Year.

EMC	FY95	FY96	FY97	FY98	FY99	FY00	FY01
AVMECH	0.050	0.131	0.141	0.097	0.038	0.018	0.046
AVTECH	0.056	0.036	0.052	0.022	0.026	0.024	---
SMPROP	0.020	0.025	0.065	0.031	---	-0.033	---
SHELEC	0.035	0.040	0.109	---	-0.031	-0.044	---
SCSYS	---	---	0.047	0.053	0.075	0.077	0.067
SOPER	---	0.044	0.102	0.028	0.019	---	---
CRYPTO	---	0.031	---	0.033	0.033	---	---
SUB	-0.040	-0.042	---	---	0.021	0.021	---
NUC	---	0.064	---	---	-0.029	---	0.093
ADMIN	---	---	---	---	---	---	---
HEALTH	---	-0.025	---	---	-0.040	---	0.036
SUPPLY	0.110	---	---	---	---	---	---
SEABEE	---	0.235	0.086	0.131	0.171	0.153	---

Note: Blank value indicates coefficient of SRBM is not significant. All values shown are significant at 0.1 level or better.

g. Unemployment

The estimated effects of civilian unemployment rate changes are positive, but significant in only 5 of the 13 models. Part of the reason for so few significant effects across the models could be the state of the national economy over the analysis time period. From 1995 to 2000 the national unemployment rate was trending downward; it was always below 5.0 percent and reached a low of 3.4 percent in 2000. [Ref. 32] The likelihood of finding a civilian job was high throughout the entire period, and small variations in such low and declining unemployment rates probably had little effect on reenlistment decisions. The significant positive partial effects of this variable on "notional" reenlistment rates range from +0.4 to +2.2 percentage points, with an average effect of increasing reenlistment by 1.0 percentage point. Over a similar time period, Hansen [Ref. 27] found that an extremely large, 5.0 percentage point, increase in the unemployment rate would increase reenlistment by only 1.0 percentage point. A study by Quester and Adedeji [Ref. 29] and another by North [Ref. 30] found reenlistment rate increases for Zone A Marines of 0.6 and 1.5 percentage points, respectively, for a 1.0 percentage point increase in unemployment.

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V. SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

A. SUMMARY

This thesis to provided information on data fields, data sources, and modeling approaches to support the development of a Retention Modeling Module (RMM) in the PerSMART data warehouse. A literature review examined existing research on turnover and retention in both civilian and military organizations. It also examined the current structure of the PerSMART data warehouse and its ability to support retention modeling. To this end, a first-term reenlistment model was estimated using data extracted from the RMS in PerSMART. Finally, alternative sources of data necessary for retention modeling were investigated.

The literature review focused on variables frequently used in prior studies to explain the retention behavior of sailors at the first-term reenlistment point. A primary focus of the literature review was the various modeling techniques that have been used in prior studies to capture the effects of military compensation on retention behavior. The vast majority of retention studies utilize an ACOL approach to explain the effect of compensation on retention behavior.

Data was extracted from PerSMART on all enlisted personnel who made the decision to reenlist, extend, or separate from the Navy during FY 1995 through FY 2001. This data was then further reduced for analysis to include only Zone A sailors who were eligible to reenlist and who had at least two but not more than six years of service. Sailors who extended their service obligations vice reenlisting for another full term were excluded from the data set.

A multivariate model was specified for the purpose of explaining the effects of military pay and bonuses on retention behavior. The model was applied to the analysis data set, which was broken down into 13 occupational groups based on the Enlisted Management Communities used by the Navy's Military Personnel Plans and Policy Division (N13). Results indicated that, for most communities, paygrade has a positive effect on reenlistment when compared to lower paygrades and a negative effect when compared to a higher paygrade. For example, an E-4 is more likely to reenlist than an E-

3 or below but less likely to reenlist than an E-5. Analysis also showed that SRBs have a significant impact on retention. Across occupational groups, the average effect of a one-level increase in the SRB multiple was a 3.5 percentage point increase in the probability of reenlistment for Zone A sailors.

B. CONCLUSIONS

Although the results of this analysis with regard to the statistical effects of SRBs on retention were significant and consistent with prior studies, the estimating model itself was limited in its ability to capture the true effects of total military compensation on retention behavior. This is in part due to the naïve use of the explanatory variable paygrade as a proxy for expected military pay. This likely led to a downward bias of the effects of SRBs due to other explanatory variables, such as family status, picking up some of the pay effects. Sailors with dependents are paid more than their counterparts with no dependents. Without a pay variable that accounts for these differences, estimates of the effect of family status on reenlistment will include the effect of the pay differential between sailors with and without dependents. The use of paygrade as an explanatory variable also does not lend itself to an evaluation of the retention impacts of various pay and other programs and policies that may be implemented by the Navy. The model used in this analysis would benefit greatly from implementing the ACOL approach to explain the effect of compensation on retention, as previous studies have done. ACOL is the generally accepted method for best capturing these effects. Additionally, although this model contained a variable for civilian employment opportunities in the form of unemployment rate changes, more comprehensive civilian comparison data, such as projected civilian earnings, are needed to better capture the effects of the economic environment on reenlistments.

Despite the limitations of this model, the analysis has shown that the current structure of PerSMART can be successfully accessed to provide most of the data required for estimating future retention models. The data fields extracted from the RMS, in particular the Time Period field (tp), were convenient for merging the data with other sources of information, such as SRB, unemployment, and basic pay tables. However, RMS can be limited by the data it receives from the EMF. The EMF is dynamic in that it

undergoes constant updating from its source inputs. These daily updates and revisions often contain errors which degrade the quality of the data contained in the RMS.

C. RECOMMENDATIONS

First, any modeling approach used to explain retention behavior should have ACOL as the key explanatory variable to capture the full effects of military compensation within the context of a structural economic model. ACOL modeling has been found to be the most precise method for predicting retention behavior, although it may be difficult to implement. Developers have indicated that an ACOL variable may not be easily automated for use in the RMS because of significant differences in how civilian earnings and military pay are included in the structure of the variable. [Ref. 28] If ACOL cannot be modeled in the RMS then a military-civilian pay ratio variable should be used. The Marine Corps in its models to forecast the impact of changes in SRB multiples currently uses this variable. [Ref. 19] Using a pay ratio variable in the RMS would require a table of current and historical civilian earnings. The civilian earnings in the Marine Corps model are the usual weekly earnings of full-time 20-to-24-year-old wage and salary workers. This information is available from the Bureau of Labor Statistics in a quarterly report titled <u>Weekly Earnings of Wage and Salary Workers</u>. [Ref. 30]

In addition to the civilian earnings requirements for a pay variable, other data sources need to be incorporated into the RMS. These include SRB, unemployment, and basic pay tables. The table used to match SRB multiples to sailors in this analysis were provided by the Center for Naval Analyses. [Ref. 31] This table includes SRB multiples by month and zone for all eligible ratings and NECs from 1977 through 2001. Current and historical unemployment data is available from the Bureau of Labor Statistics website. [Ref. 32] This website provides local, state, and national unemployment information by month and year for nearly every combination of demographics and occupational areas. If future models use state unemployment information the EMF field "HOME_OF_RECORD" will need to be included in the RMS to match rates to individuals. The Defense Finance and Accounting Service has a website with military pay tables dating back to 1949. [Ref. 38] Their website also provides information on all other forms of compensation including housing allowances and special pays.

Incorporating these data requirements and a sophisticated variable like ACOL into the RMS will make it an invaluable asset to analysts as well as policy makers. Having a near-real-time decision support system such as this will enable the Navy leadership to make better informed policy decisions regarding the implementation of pay and retention programs and their effects on Navy retention.

APPENDIX. RMS EXTRACT DATA FIELDS

The following is an alphabetical listing and description of the data fields in the RMS data extract available for this analysis. Several fields are associated with a time period for an event. These time periods are used as a means to compare event dates and consist of a four-digit number that represents a specific month and year. For example, time period number 1153 equates to January 1996. Based on this, time period number 1152 equates to December 1995, and number 1154 equates to February 1996.

Data Field	Description
Adsd	Active Duty Service Date.
Adsd_Tp	Time period for Adsd.
Br_Cl	Branch and Class of Service.
Ced	Current Enlistment Date.
Ced_Tp	Time period for Ced.
Date_Of_Birth_Actual	Birth date of member as per contract.
DecisionFiscalYear	Fiscal year of decision to reenlist/extend/separate
Dod_Loss_Code	Type and reason for release from active duty or separation.
Eaos	Expiration of Active Obligated Service.
Eaos_Tp	Time period for Eaos.
Enl_Mgmgt_Community	Enlisted management community.
Ethnic_Group_Actual	Ethnic group for individual.
Individual_Id	RMS database identifier for individual.
LOS	Length of Service.
Lcdo_Tp	Time period for Loss_Change_Date_Of_Occurrence.
Loss_Change_Date_Of_ Occurrence	Date of loss from the Navy.
Loss_Chg_Code	Navy Loss Code for reason member was lost.
Navy_Loss_Rqc	Recommendation of last duty station regarding the reenlistment of member.
Nbr_Dep_Residing_ In_ Household	Total authorized dependents sponsor has residing with him/her at current duty station.
Nec1 *to* Nec10	Navy Enlisted Classification code assigned to member.
Nec_Tp1 *to* Nec_Tp10	Time period associated with respective Nec.
Oex	Length in months of current operative extension to enlistment.
Oex_Date	Operative extension effective date.
Oex_Date_Tp	Time period for Oex_Date
Onboard_Actual_Uic	UIC for activity to which member is currently assigned.
Onboard_Ss	Sea/shore duty code for onboard activity.
Pebd	Pay Entry Base Date.
Pebd_Tp	Time period for Pebd.
Pres_Rate_Code_1_4	4-digit code identifying member’s present rating.

Data Field	Description
Pres_Rate_Code_Pg	Code identifying member's present paygrade.
Pri_Dep	Number and type of primary dependents (spouse and children) member has.
Race_Actual	Race code for individual.
Sec_Dep	Number and type of secondary dependents (parents) the member has.
Sex_Actual	Gender.
Soft_Eaos	Terminal date of member's total active duty obligation; includes executed agreements to extend enlistment.
Soft_Eaos_Tp	Time period for Soft_Eaos
Srb_Level	Multiplier in effect at the time the member's entitlement to SRB was established.
Srb_Skill_Rating_Assgn	Indicates whether or not the member is serving in a rating or NEC on which entitlement to SRB is based.
Srb_Zone_Ind	Zone of SRB eligibility of member.
Ssn_Actual	Social Security Number
code	Code assigned to member during RMS data extract to identify event as reenlistment, extension, or separation.
los_date	Beginning date used to establish LOS.
los_tp	Time period for los_date.
tp	Time period of reenlistment decision.

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